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MODELLING TRAVEL BEHAVIOUR WITH SHARED MICRO-MOBILITY SERVICES AND EXPLORING THEIR ENVIRONMENTAL IMPLICATIONS

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ABSTRACT

The convergence of recent developments in electrification, connectivity and the sharing economy has enabled several new mobility services to emerge. Among them, shared micro-mobility services (e.g., e-scooters, e-bikes) have seen particularly fast international rollouts. Given their rapid diffusion, effective regulation and integrated transport planning is pertinent. City administrations are further asking how shared micro-mobility services can contribute to increasingly stringent CO_2 reduction targets.

Advances in these directions are hindered by our limited understanding of travel behaviour. In particular, we do not yet comprehensively understand who uses shared micro-mobility services and how users choose between these and more established modes (e.g., public transport, private cars).

This thesis contributes by offering some of the first empirical evidence on users, mode choice, substitution patterns and net CO_2 emissions of shared micro-mobility services. It goes beyond previous work by presenting comprehensive evidence for several different shared micro-mobility services in a single city, by estimating the first mode choice models between them based on revealed preference data, and by demonstrating how to use emerging data sources such as vehicle and human GPS traces to estimate such models at very high spatiotemporal resolutions.

For Zurich, Switzerland, this dissertation finds that users of shared micro-mobility services tend to be young, university-educated males with full-time employment living in affluent households without children or cars. Mode choice is strongly influenced by trip distance, precipitation and access distance. *Shared* e-scooters and e-bikes mostly replace walking, cycling and public transport. Hence, they emit more CO_2 than the transport mode mix they replace. *Personal* e-scooters and e-bikes replace car-based modes substantially more often. Hence, they emit less CO_2 than the transport mode mix they replace and contribute to making urban transport more sustainable.

These results have implications for research, policy and practice. First, they build the foundation for incorporating shared micro-mobility services into larger transport simulations. This, in turn, allows estimation of their impact at scale and enables testing the effectiveness of policy interventions. Second, this

dissertation presents nuanced empirical evidence for city administrations that aim to evaluate how shared micro-mobility services contribute to transport-related CO_2 emissions. The third implication of this research is to elucidate promising avenues for service providers to optimize their fleet operations.

ZUSAMMENFASSUNG

Die Konvergenz von Forschung und Entwicklung in den Bereichen Elektrifizierung, Konnektivität und der «Sharing Economy» hat jüngst das Aufkommen unterschiedlicher neuer Mobilitätsdienste ermöglicht. Darunter fallen auch geteilte Mikromobilitätsdienste (z.B. E-Trottinetts, E-Bikes), die in den vergangenen Jahren besonders schnell international verbreitet wurden. Angesichts der Geschwindigkeit und Tragweite dieser Entwicklung sind wirksame Regulierung und integrierte Verkehrsplanung von besonderer Bedeutung. Es ist darüber hinaus unklar, wie geteilte Mikromobilitätsdienste zur Reduktion städtischer CO_2-Emissionen beitragen können.

Fortschritte bei diesen Herausforderungen werden vor allem durch unser limitiertes Verständnis von der Nutzung geteilter Mikromobilitätsdienste gehemmt. Insbesondere ist bisher noch nicht erforscht, welche soziodemografischen Hintergründe die Nutzer von geteilten Mikromobilitätsdiensten haben, und wie Nutzer zwischen den verschiedenen geteilten Mikromobilitätsdiensten und etablierteren Verkehrsmodi (z.B. ÖPNV, PKW) wählen. Insbesondere die Erklärung des Verkehrsmittelwahlverhaltens ist eine notwendige Voraussetzung für die Integration geteilter Mikromobilitätsdienste in Verkehrssimulationen und damit für eine wirksame integrierte Verkehrsplanung in Wissenschaft und Praxis.

Diese Dissertation liefert erste empirische Erkenntnisse zu Nutzern, Verkehrsmittelwahl, Substitutionsmustern und Netto-CO_2-Emissionen geteilter Mikromobilitätsdienste. Neu ist dabei insbesondere der Umfang der Erkenntnisse (Vergleich mehrerer verschiedener geteilter Mikromobilitätsdienste in einer einzigen Stadt), die kreative Erhebung und Nutzung neuer Datenquellen (GPS-Daten von Smartphones und Fahrzeugen), sowie die Schätzung der ersten Verkehrsmittelwahlmodelle überhaupt zwischen mehreren verschiedenen geteilten Mikromobilitätsdiensten sowie etablierteren Verkehrsmodi.

Alle Analysen wurden mit Daten aus Zürich (Schweiz) durchgeführt. Die Ergebnisse zeigen, dass Nutzer geteilter Mikromobilitätsdienste tendenziell junge Männer mit Hochschulabschluss und in Vollzeitbeschäftigung sind, die

in wohlhabenden Haushalten ohne Kinder oder PKWs leben. Die Verkehrsmittelwahl hängt stark von der Fahrtdistanz, dem Niederschlag und der Zugangsdistanz ab. Geteilte E-Trottinetts und E-Bikes ersetzen auf den meisten Strecken nachhaltigere Verkehrsmittel (zu Fuss, Velo, öffentlicher Nahverkehr), während private E-Trottinetts und E-Bikes auch deutlich häufiger den PKW ersetzen. Auf ihren gesamten Lebenszyklus gesehen erzeugen geteilte E-Trottinetts und E-Bikes somit mehr CO_2 Emissionen als die Verkehrsmodi, die sie ersetzen, während private E-Trottinetts und E-Bikes zu einer Reduktion der städtischen CO_2-Emissionen beitragen.

Diese Ergebnisse bilden die Grundlage, um geteilte Mikromobilitätsdienste in Verkehrssimulationen zu integrieren und so ihre Auswirkungen auf Verkehr und Raum in grösserem Umfang abzuschätzen, sowie die Wirksamkeit planerischer und regulatorischer Massnahmen zu testen. Darüber hinaus bietet diese Dissertation umfangreiche empirische Erkenntnisse zu den Netto-CO_2-Emissionen geteilter und privater Mikromobilitätsfahrzeuge, die Stadtverwaltungen als Basis für Entscheidungen zur Subvention oder Regulierung letzterer nutzen können. Zuletzt können auch Anbieter geteilter Mikromobilitätsdienste die Ergebnisse dieser Dissertation nutzen, um den Betrieb ihrer Fahrzeugflotten zu optimieren.

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CONTENTS

1. INTRODUCTION

1.1 MOTIVATION

Climate change is a defining issue of our time. The transport sector contributes substantially to climate change by emitting 23% of global energy-related CO_2 emissions (IEA, 2021). Whereas other sectors have succeeded in halting or reducing their CO_2 emissions, rising numbers are reported for the transport sector year by year. This is largely due to rising global transport demand, which is projected to more than double by 2050 when compared to 2015 (ITF, 2021).

Cities face particularly pronounced challenges with regards to transport in the near future. One of the main reasons is urbanization. The share of the global population living in urban settlements is projected to increase from 56% in 2020 to 68% in 2050 (UN, 2021). This development will put further strain on urban transport systems, which already often operate at maximum capacity today with high levels of road congestion and public transport crowding during rush hours. Extensions and redesigns of urban transport systems, however, are difficult and costly due to spatial constraints. At the same time, congestion stifles economic growth, limits agglomeration economies and implies many lost hours for citizens (Goodwin, 2004; Graham, 2007). As Arnott and Small (1994: 446) pointedly write: "Time spent ensnarled in traffic is not simply time wasted; for most of us, it is time miserably wasted." The redesign of urban transport towards greater spatial efficiency and environmental sustainability is therefore imperative.

In parallel, recent developments in electrification, connectivity and the sharing economy have enabled the emergence and diffusion of several new[1] mobility services (e.g., bikesharing, carsharing, ride-hailing) and transport modes (e.g., e-scooters, e-bikes). Micro-mobility is one subcategory of such (new) transport modes that comprises "vehicles with a mass of no more than 350 kg and a design speed no higher than 45 km/h" (ITF, 2020b). Given their compact size and their electric propulsion, micro-vehicles such as e-bikes and e-scooters

[1] It has to be noted, though, that not all "new" mobility services or "new" transport modes are actually new. One example includes e-scooters that were already introduced about than 100 years ago (Wild, 2015). In such cases, what is "new" is the updating and the wide-spread adoption of a transport mode introduced earlier.

hold substantial potential to make urban transport more environmentally sustainable and more spatially efficient. First, they emit substantially less CO_2 than other transport modes. A recent life-cycle assessment of the CO_2 emissions of different transport modes showed that private[2] e-bikes and private[2] e-scooters, on average, emit 34g and 42g CO_2 per person kilometre (pkm), respectively (ITF, 2020a). In comparison, public transport emits between 64g and 91g CO_2 per pkm and private cars emit between 124g and 162g CO_2 per pkm (ITF, 2020a). Second, micro-vehicles are substantially smaller than private cars. Hence, they consume less parking space but also less road space when moving. Third, micro-mobility could extend the catchment area (and mode share) of public transport by shortening the access and egress travel times. Access and egress to public transport (also known as the "first/last mile") has long been known as a substantial deterrent to public transport use. However, it remains difficult to solve due to the spatiotemporally dispersed nature of demand.

While other forms of micro-vehicles such as bikes and non-electric kick-scooters have been part of urban transport for long, the presence of e-scooters and e-bikes has drastically increased in the past few years. This is due to the plethora of investor-backed shared micro-mobility companies (e.g., Lime, Bird, Tier, Voi) that have started to roll-out their services globally. US ridership surged accordingly with 35 million rides reported for 2017, 84 million for 2018 and 136 million for 2019 (NACTO, 2020). The rapid expansion of shared micro-mobility services has not been without controversy: chaotic scenes with unused shared e-scooters clogging sidewalks were often observed in major cities worldwide (Figure 1), operational services (e.g., rebalancing and recharging) add further CO_2 emissions, and vehicles are typically deployed in dense city centres where many alternative transport modes are already available. This development continues to challenge city administrations and transport planners as the empirical evidence needed to develop appropriate regulation for and to predict the impact of shared micro-mobility services is still missing. In particular, empirical evidence along the three transport policy dimensions sustainability, equity and spatial efficiency is needed to comprehensively answer frequently asked questions such as "Should city administrations allow shared

[2] The distinction between "private" and "shared" is important in the context of life-cycle CO_2 assessments as shared vehicles typically incur further CO_2 emissions due to operational services (e.g., recharging, repositioning). Shared vehicles also have shorter lifespans than privately owned vehicles, implying higher CO_2 emissions per pkm due to manufacturing when averaged over the entire lifespan.

micro-mobility services to operate within their jurisdiction?" I reflect on the evidence collected in this thesis in the context of this particular question in Chapter 5.2.

Figure 1 Unused shared e-scooters clogging sidewalks in Dortmund, Germany.

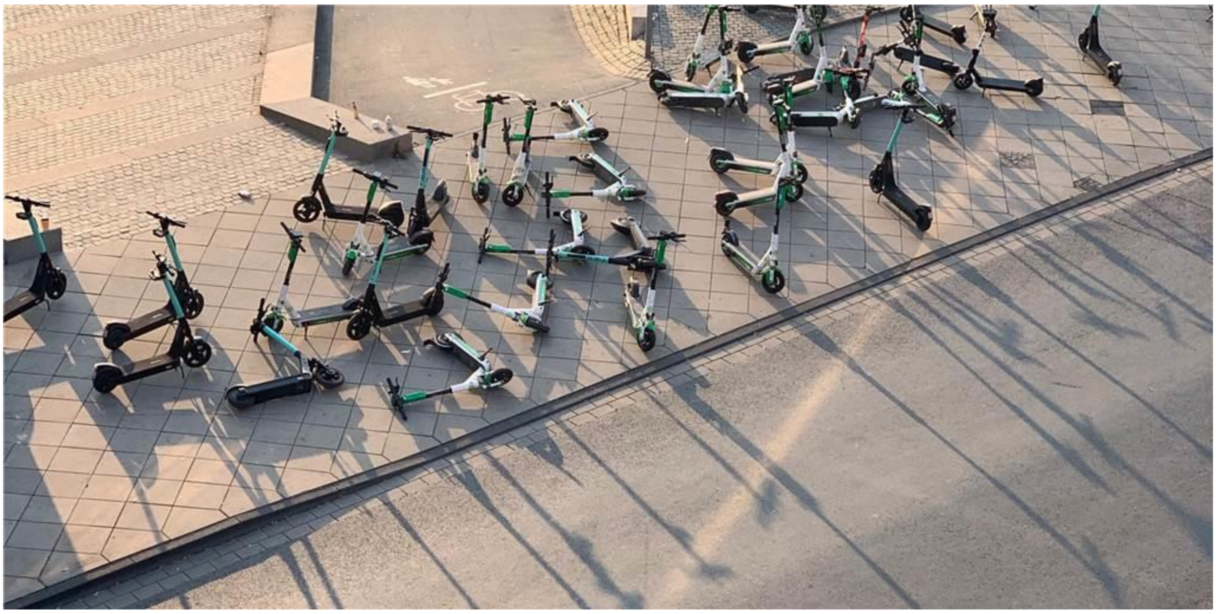


Image source: https://www.ruhrnachrichten.de/dortmund/e-scooter-chaos-am-phoenix-see-bremst-rollstuhlfahrer-aus-plus-1547609.html

This thesis contributes by establishing an empirical evidence base for a number of pressing research questions on shared micro-mobility, using the city of Zurich (Switzerland) as a case study. A particularly comprehensive documentation of relevant research questions at the time of conducting this research can be found in two successive Calls for Papers (2020, 2021) from the journal *Transportation Research Part D: Transport and Environment*. The most relevant research questions to this thesis from the 2020 Call for Papers are reiterated here:

- "Use of shared micro-mobility: How does the use of different shared micro-mobility modes (e.g., bikes vs. e-bikes vs. e-scooters) differ across space and time? How can big data and new methods be used to advance our understanding of shared micro-mobility behavior?"
- "Correlates of shared micro-mobility: Who uses shared micro-mobility services? Do shared micro-mobility services benefit certain social groups more than others? Are there any equity concerns?"

- "Interactions with other modes: How do shared micro-mobility services affect the use of other transport modes? What is their potential for mode substitution in the long term? What are their traffic and environmental impacts?"

This thesis comprises the following three original papers that respond to these research questions:

1) Reck, D.J., H. Haitao, S. Guidon and K.W. Axhausen (2021) Explaining shared micro-mobility usage, competition and mode choice by modelling empirical data from Zurich, Switzerland, *Transportation Research Part C: Emerging Technologies*, **124**: 102947.
2) Reck, D.J. and K.W. Axhausen (2021) Who uses shared micro-mobility services? Empirical evidence from Zurich, Switzerland, *Transportation Research Part D: Transport and Environment*, **94**: 102803.
3) Reck, D.J., H. Martin and K.W. Axhausen (2021) Mode choice, substitution patterns and environmental impacts of shared and personal micro-mobility, *Transportation Research Part D: Transport and Environment* (submitted: 8 July 2021).

Each paper is briefly summarized in the following subsection to give the reader an overview of their main contributions. Methodologically, all papers employ discrete choice models (Train, 2003). These include multinomial logit and mixed logit models to analyse transport mode choice (Hensher and Greene, 2003; McFadden, 1974; McFadden and Train, 2000), as well as univariate and multivariate probit models to analyse user characteristics (Becker et al., 2017; Choo and Mokhtarian, 2008; Greene, 2012; Yamamoto, 2009). For further details, I refer to the papers themselves (Chapters 2-4 of this thesis).

1.2 SUMMARY OF PAPERS

1.2.1 Explaining shared micro-mobility usage, competition and mode choice by modelling empirical data from Zurich, Switzerland

The first paper (Chapter 2) of this thesis develops a new methodology to model and analyse shared micro-mobility usage, competition and mode choice at a high spatiotemporal resolution using widely accessible vehicle location data.

Prior work on shared micro-mobility comprises studies on single modes and comparative studies between two modes that focus on aspects such as user or trip characteristics. While these studies provide valuable evidence for many purposes, they are of limited use to understanding why and how users choose between shared micro-mobility services. Information on mode choice, however, is essential for transport planning as it enables the incorporation of shared micro-mobility services into transport simulations to assess and predict their impact at scale and under different policy scenarios.

We address this gap by

- collecting a large data set (169 million observations) of vehicle GPS traces for four different shared micro-mobility services in Zurich,
- developing a generally applicable methodology to reconstruct trips and choice sets from these GPS traces, and
- estimating a first mode choice model between four different shared micro-mobility services.

Data is collected in Zurich, Switzerland. Several different shared micro-mobility services are operating in the city, making it a suitable place for analysis. These include docked bikes and e-bikes (Publibike), dockless e-bikes (Bond) and dockless e-scooters (e.g., Lime, Bird, Tier, Voi). For two months in early 2020, we queried openly accessible APIs of five different providers every ~60 seconds for all available vehicles, thus collecting over 169 million observations. Each observation contains, amongst others, a vehicle ID, a timestamp, and the vehicle's GPS coordinates. Each vehicle and its movements in space and time can be described as a sequence of observations. However, each vehicle only appears in our data set when it is available to be booked. Hence, we can define a gap in observations that satisfies certain criteria as a trip. We obtain a final number of 168 895 shared micro-mobility trips during the two months of data collection (~2 800 per day). For each such trip, we next define a choice set (i.e., collection of available options the user could have chosen from) using the data obtained for all available vehicles from other providers nearby. Finally, we estimate several mode choice models using all available information on the vehicles themselves (company, battery charge), the trips conducted (time of day, distance, elevation, price) and the vehicle density for each provider at the origin of each trip.

The estimated models show that mode choice is dominated by distance and time of day. Docked (e-) bikes are preferred during morning and afternoon peaks, which suggests commuting use. Dockless e-scooters show the opposite pattern: they are preferred during midday and night. Our results further reveal a "plateau effect" with decreasing marginal utility gains for increasing fleet densities. In other words, while increasing the number of available vehicles initially yields more bookings, marginal utility gains are decreasing up to a level of indifference, where increasing fleet densities do not increase choice probability any further. This effect applies to all analysed shared micro-mobility services, however it is particularly pronounced for dockless e-scooters and e-bikes.

This study contributes by showing how new data sources can be used to advance our understanding of travel behaviour with emerging transport modes. It builds the foundation for incorporating shared micro-mobility services into transport simulations by estimating a first mode choice model between several such services. City authorities can use the quantitative relationship between vehicle density and usage for evidence-based regulation of shared micro-mobility fleet sizes to prevent unnecessary clogging of public space. Our results further suggest that docked modes are preferred for commuting. Docking infrastructure for currently dockless modes could hence be vital to fostering their use during morning and afternoon peaks. This, in turn, could reduce road congestion or crowding in public transport.

Finally, this study has some limitations. Most importantly, it is limited to shared micro-mobility services. Further studies that include more established transport modes (e.g., public transport, private cars and bikes, walking) are needed to extend the findings of this research with an even more holistic mode choice model. Due to the data collection method employed, information on users was also not available. Yet, it is well established that socio-economic characteristics influence mode choice. Hence, future studies building on different data sets could include such information to develop a more comprehensive understanding of shared micro-mobility mode choice.

1.2.2 Who uses shared micro-mobility services? Empirical evidence from Zurich, Switzerland

The second paper (Chapter 3) of this thesis begins where the first paper (Chapter 2) ends: it reports on a large survey conducted in Zurich to investigate the socio-economic characteristics of users of shared micro-mobility services.

Understanding users of shared micro-mobility services is relevant not only to inform modelling and prediction but also to inform practical transport planning and policy making. This is because users will be the main beneficiaries of pending public investments in transport infrastructure (e.g., micro-mobility recharging stations) and reallocations of public space (e.g., e-scooter parking spots, new bike lanes). Without understanding the socio-economic profile of users of different shared micro-mobility services, it is impossible to assess whether any equity concerns arise and how to address them responsibly.

Most prior work has focused on users of docked bike-sharing schemes. At the time of conducting this research, little was known about users of newer shared micro-mobility schemes (e.g., dockless e-bikes, dockless e-scooters). In particular, previous studies did not compare users of several different services in a single location. This is relevant, however, as context (e.g., weather, geography) is well known to influence transport mode choice. Hence, comparisons of users of different services in different locations might be biased.

We address this gap by conducting a large-scale survey among 17 500 randomly selected inhabitants of Zurich, Switzerland, to elicit information on account holders[3] and users[3] of three different shared micro-mobility schemes (dockless e-scooters, dockless e-bikes, docked (e-) bikes) as well as on socio-economic characteristics. Between July and August 2020, 1 454 (8%) complete responses were collected. First, we analysed and compared the socio-economic characteristics of users of different services with those of the wider population descriptively. Second, we modelled usage individually and jointly and estimated (multivariate) probit models. The multivariate probit approach allows error terms between individual choices to be correlated and is thus commonly used to model interrelated usage and vehicle / public transport season ticket ownership.

Our results show several similarities of shared micro-mobility users in comparison to the general population. Shared micro-mobility users tend to be young and highly educated males. They further tend to be full-time employed and tend to live in households without children or cars. Exceptions from these general patterns nuance the user groups of different shared micro-mobility

[3] Account holders do not necessarily have to be users of shared micro-mobility schemes. However, only the analysis of users allows drawing conclusions on the inclusiveness of shared micro-mobility schemes. Here, we asked all participants both for information on accounts and on the frequency of usage. As expected, the share of active users (those who use a particular service at least several times each month) is substantially lower than the share of account holders. For example, only 44% of all account holders of shared e-scooter schemes are active users. All further analyses were hence conducted with active users only to avoid potential biases.

services. In Zurich, users of shared e-scooters are particularly young (mean: 33 years) while users of dockless e-bikes are substantially older (mean: 39 years). At the same time, more females use shared e-scooters (32%) than dockless e-bikes (18%). We further find that users of shared e-scooters are more similar to the general population than their bike-sharing peers in three other socio-economic characteristics: educational attainment, full-time employment and household income. This last observation could be only of temporary nature, however, as a higher share of shared e-scooter users are university students and shared e-scooter schemes have only operated in Zurich for three years now.

This study contributes by providing a current socio-economic profile of users of three different shared micro-mobility services in a single location. As such, it is a first step towards understanding who will benefit from pending public investments in infrastructure dedicated to these new modes. The results confirm that equity is a justified concern in the context of shared micro-mobility services. Especially inclusiveness of usership along gender, age, educational and income divides may be difficult to achieve and thus requires careful considerations by cities planning to launch shared micro-mobility schemes. Policy makers can increase *equity in access* to shared micro-mobility services as a first step towards *equity in usage* by requiring all service providers to redistribute their vehicles evenly in a city by measure of population density.

Finally, this study has limitations. Despite sending our survey to a sizable randomly drawn initial sample (17 500) and receiving 1 454 complete responses, the subgroups of active shared micro-mobility users were quite small (n = 73, 178 and 207). This sampling approach has the advantage of reducing potential sampling biases. However, the small numbers also reduce the complexity of possible models in terms of the number of variables that can be tested. Future studies could use more targeted sampling techniques to test our findings and extend them.

1.2.3 Mode choice, substitution patterns and environmental impacts of shared and personal micro-mobility

The first paper (Chapter 2) of this thesis investigated mode choice between different shared micro-mobility services. The second paper (Chapter 3) investigated socio-economic user characteristics of different shared micro-mobility services. The final and third paper (Chapter 4) of this thesis extends the previous two by

- collecting a large data set with matching GPS tracks, booking data and survey data for 540 travellers over the course of three months,
- estimating a first comprehensive choice model between eight different transport modes (incl. shared and personal e-scooters and e-bikes), and
- calculating distance-based substitution rates and net CO_2 emissions for shared and personal e-scooters and e-bikes.

Data was collected as part of a joint project with Swiss Federal Railways between June and October 2020. In June 2020, we sent 10 000 invitations to residents of Zurich, Switzerland. Participation in our study included two surveys and three months of GPS tracking, and was incentivized with 90 CHF[4]. A total of 540 (6%) participants completed the entire study.

All participants used the smartphone app "MyWay" (available in app stores) to track their travel behaviour for three months (July to October 2020). The app passively collects GPS traces, identifies trips and induces transport modes based on automatic comparisons with public transport timetables and past travel behaviour. Each day, participants were asked to verify past trips and to modify inaccuracies. Using this method, a total of 65 716 trips were recorded for all participants. This number further divides into 17 004 public transport trips, 16 211 car trips, 15 393 walking trips, 14 246 bike trips, 2 537 e-bike trips, and 345 e-scooter trips. We further divide e-bike and e-scooter trips into *private* and *shared* e-bike and e-scooter trips by matching the GPS tracks with booking data obtained for our participants through the partnership with Swiss Federal Railways. 287 (11%) of the e-bike trips and 121 (35%) of the e-scooter trips had matching booking records and were thus labelled as shared e-bike / shared e-scooter trips, respectively.

Finally, we add contextual data to each conducted trip. This includes weather data (e.g., precipitation, wind speed), socio-economic characteristics of the person conducting the trip (e.g., age, gender, public transport season tickets, household vehicle ownership) and the availability of shared micro-mobility vehicles at the start of the trip[5]. For each trip, we also compute the non-chosen alternatives by using the agent-based transport simulation software MATSim (Horni et al., 2016). The MATSim Zurich scenario has been extensively used in transport research (e.g., Balac et al., 2019; Becker et al., 2020; Hörl et al., 2021; Manser et al., 2020). In comparison to the first paper of this thesis, the

[4] 1 CHF = 1.11 USD at the time of writing (16 June 2021).

[5] Swiss Federal Railways records the locations of all shared micro-mobility vehicles in Zurich in five-minute intervals through the providers' APIs.

data structure here allows to account for taste heterogeneity in mode choice between individuals. We thus chose a mixed logit model in panel structure with random alternative-specific constants.

The estimated model shows that trip distance, precipitation and access distance are fundamental to micro-mobility mode choice. In comparison to the reference mode (walking), longer trip distances increase mode choice for all other modes. Precipitation negatively influences mode choice for all modes except for public transport and private cars. The penalty is highest for shared e-bikes and e-scooters. Increasing access distances influence mode choice negatively for public transport and shared e-bikes / e-scooters. The penalty for shared e-scooters (-6.16) is substantially higher than for shared e-bikes and public transport (-2.36 and -2.31, respectively) and users are willing to walk an average of 60m and a maximum of 200m to access a shared e-scooter. This difference in access distance penalties could be due to the absence of reservation features for shared e-scooters, which increases users' uncertainty regarding mode availability. Shared e-bikes can be reserved for up to ten minutes in Zurich and real-time information about public transport vehicle locations is available in common trip planning apps (e.g., Google Maps). By adding a reservation feature, shared micro-mobility providers could subsequently increase the catchment area of each individual vehicle.

We next use the estimated model to derive distance-based substitution rates for shared and personal e-scooters and e-bikes. We do so by setting the availability of the chosen mode to zero for all trips conducted, and by predicting the (substituting) mode for these trips with the previously estimated model. In comparison with other commonly used methods to elicit substitution rates such as survey-based questions, this method allows for the calculation of precise and distance-based substitution rates (vs. trip-based substitution rates) and takes into account underlying user preferences.

We find that *personal* e-bikes replace trips conducted with all four main transport modes (walking, public transport, car, bike) while *shared* e-bikes replace fewer car trips and more public transport and bike trips. This difference is particularly pronounced for longer distances, while both modes mostly replace walking for short distances (i.e., below 1 km). We find a similar pattern for personal and shared e-scooters. Compared to personal e-bikes, personal e-scooters replace more walking and fewer car trips while shared e-scooters predominantly replace walking and public transport trips.

As a final step, we use the results of a recently conducted life-cycle assessment of the CO_2 emissions of different transport modes (ITF, 2020a) to calculate the net CO_2 emissions (i.e., after accounting for substitution rates) of shared and personal e-scooters and e-bikes. We find that personal e-bikes and e-scooters emit less CO_2 than the transport modes they replace, while shared e-bikes and e-scooters emit more CO_2 than the transport modes they replace.

City administrations aiming to reduce transport-related CO_2 emissions can use these insights to justify subsidies for personal micro-mobility (e-bike / e-scooter) sales and investments in cycling infrastructure. The research findings further caution city administrations from admitting and licensing shared micro-mobility providers to reduce CO_2 emissions. To achieve this end, operational services and vehicle manufacturing of shared micro-mobility services would have to be further optimized. One solution could be recharging stations near public transit hubs combined with incentives (bonus minutes) for users to drop off vehicles with low batteries there. This would not only decrease the operational CO_2 emissions of shared micro-mobility services, but also enable intermodal trips with public transport and improve parking organization of otherwise free-floating vehicles. Last but not least, shared micro-mobility services could help to spark sustainable mobility transitions in the long-term if usage leads to ownership. More research is needed, however, to establish these effects.

Finally, this study has some limitations. Most importantly, it uses the gross CO_2 emissions as calculated in the ITF (2020a) life cycle assessment for Paris. While this is the most comprehensive life cycle assessment to date, CO_2 emission are likely to differ between Paris and Zurich for some transport modes while they can be assumed to be similar for others (e.g., the same companies offer shared e-scooter services in both cities). Future work could address this shortcoming by collecting and combining data from a single place using the methods proposed in this paper. Another limitation is the influence of COVID-19 as data collection for this study was conducted in summer 2020. Although incidence rates were comparatively low in Zurich during this time, travel behaviour was still affected and public transport usage remained lower than usual. Our study thus potentially over-estimates public transport substitution by other modes.

1.3 OUTLINE OF THESIS

This thesis is structured in five chapters. The introduction (Chapter 1) is followed by the three original research papers (Chapters 2 to 4). Chapter 5 concludes, reflects and outlines directions for future work.

2. EXPLAINING SHARED MICRO-MOBILITY USAGE, COMPETITION AND MODE CHOICE BY MODELLING EMPIRICAL DATA FROM ZURICH, SWITZERLAND

A version of this chapter is published as: Reck, D.J., H. Haitao, S. Guidon and K.W. Axhausen (2021) Explaining shared micromobility usage, competition and mode choice by modelling empirical data from Zurich, Switzerland, *Transportation Research Part C: Emerging Technologies*, **124**: 102947.

ABSTRACT

Shared micro-mobility 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 spatiotemporal resolution for more than two modes. To this end, we develop a generally applicable methodology to model and analyse shared micro-mobility 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 micro-mobility modes using the largest and densest empirical shared micro-mobility data set to-date. 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 micro-mobility 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 micro-mobility regulation and optimise their fleet deployment, respectively.

2.1 INTRODUCTION

Recent technological development has accelerated the emergence of shared micro-mobility 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 companies. Meanwhile, policy makers are often struggling to develop pertinent regulation as the usage of shared micro-mobility 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 micro-mobility 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 limited but increasing at a fast pace (e.g., Campbell et al., 2016; Du et al., 2019; Guidon et al., 2019; He et al., 2019; Shen et al., 2018; Xu et al., 2019; Yang et al., 2019). Dockless e-scooters are the latest addition to the micro-mobility 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 data sets of a single shared micro-mobility 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 micro-mobility 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 micro-mobility modes in transport network simulations to analyse (and predict) their impact at the system level (where micro-mobility 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 policy making (e.g., vehicle licensing, parking space allocation). Third, it provides insights into trade-offs and marginal effects, enabling existing service providers to further optimize their operations (e.g., vehicle repositioning and charging by time of day) and prospective service providers to evaluate their competitive positions.

To this end, this paper estimates the first mode choice models between four different shared micro-mobility 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 micro-mobility 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 company 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 micro-mobility modes in Zurich using the largest and densest empirical shared micro-mobility data set to-date.

The remainder of this article is organised as follows. In Section 2, we review the literature on shared micro-mobility with a particular focus on usage and mode choice. In Section 3, we introduce our data set 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.

2.2 LITERATURE REVIEW

The number and variety of shared micro-mobility 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 micro-mobility 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 micro-mobility 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 (external and trip-related factors) are most relevant to the topic of this paper (as we do not have information about users) and thus the focus of this literature review.

Research analysing external and trip-related factors that influence demand for shared micro-mobility 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 scholary 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 micro-mobility mix. Only few peer-reviewed academic studies examine external factors influencing user demand. Most studies have been conducted using the publicly available booking data sets from Louisville (KY) and Austin (TX) (Bai and Jiao, 2020; Caspi et al., 2020; Noland, 2019; Noland, 2021; Reck et al., 2021b) or by scraping the operators' openly accessible APIs (e.g., Espinoza et al., 2020; Hawa et al., 2021; 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., 2021; Reck et al., 2021b; Zuniga-Garcia and Machemehl, 2020). Also, trips are relatively short. For example, the median distance for Louisville, is 1.3

km (Reck et al., 2021b). Precipitation, low temperatures and wind negatively influence their usage (Noland, 2021). 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., 2021b). 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., 2021b).

While most previous studies employ data sets of a single shared micro-mobility 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 five-minute 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 data sets from 02/2018 for one company 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 companies) and shared docked bike trips (Capital Bikeshare) in Washington, D.C. Using data from the companies' 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 users 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 micro-mobility 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 micro-mobility 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 micro-mobility 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., one to five-minute 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 micro-mobility services are used anywhere outside of the US as rigorous peer-reviewed studies have not appeared yet. Thus, a comprehensive comparison of many different micro-mobility 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 micro-mobility 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 four different shared micro-mobility modes leveraging the largest and densest empirical shared micro-mobility data set to-date.

2.3 DATA

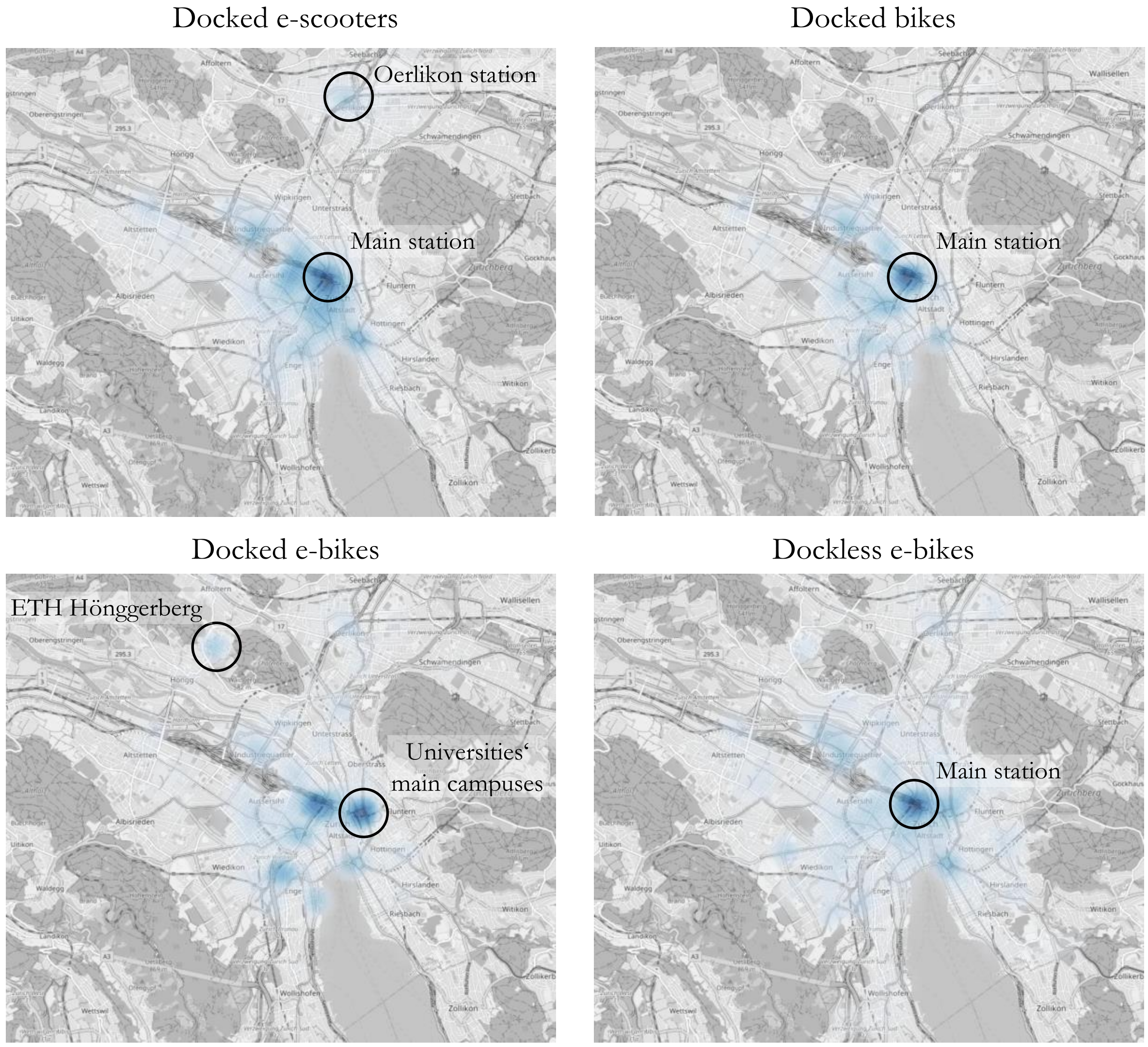
2.3.1 Collection

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 micro-mobility companies 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 companies started operating since 2019, among them Lime, Bird, Tier, Voi and Circ.

Our raw data set consists of vehicle location data from four shared micro-mobility companies offering four different shared micro-mobility services in Zurich, Switzerland. Between 1 January and 29 February 2020, we queried each micro-mobility company's 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 company and, for dockless modes, the battery charge. Each vehicle appears as a sequence of observations over time in our data set 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 two minutes and at most one 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. We further identify and remove falsely identified trips due to operator actions (i.e., battery loading, rebalancing, and repairs) with the following steps. (1) Remove trips where the battery charge is higher at the end of the trip than at the start of the trip (battery loading). (2) Remove trips where more than two vehicles simultaneously reappear in close proximity (rebalancing). Finally, repairs are conducted at special workshops and require more than 1h from pick-up to redistribution, hence such trips were already removed by the maximum trip duration of 1h.

We obtain 168 895 micro-mobility trips during the two months of analysis (~ 2 800 trips per day) after the described preprocessing steps. A first visual impression of the spatial distribution of destinations by mode can be obtained from Figure 2. We observe that dockless e-scooters and docked bikes are mostly used in Zurich's city centre with clear hotspots at the main public transport stations. Docked e-bikes show additional hotspots at the universities' main campuses in the city centre and the technical university's outer city campus ETH Hönggerberg. Dockless e-bikes show the broadest spread across the city.

Figure 2 Heatmap of frequent destinations by shared micro-mobility mode.



2.3.2 Validation

We validate the calculated trips by comparing them to booking data which we obtained for three of the four modes (docked e-bikes, docked bikes, dockless e-bikes). For each trip, we compare origin/destination, weekday, time of day and duration. Overall, we correctly identified ~95% of all trips. The only bias that we detected is fewer short rides for docked e-bikes and bikes (5-12 minutes) and slightly more longer trips (17+ minutes), 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.

2.3.3 Descriptive analysis

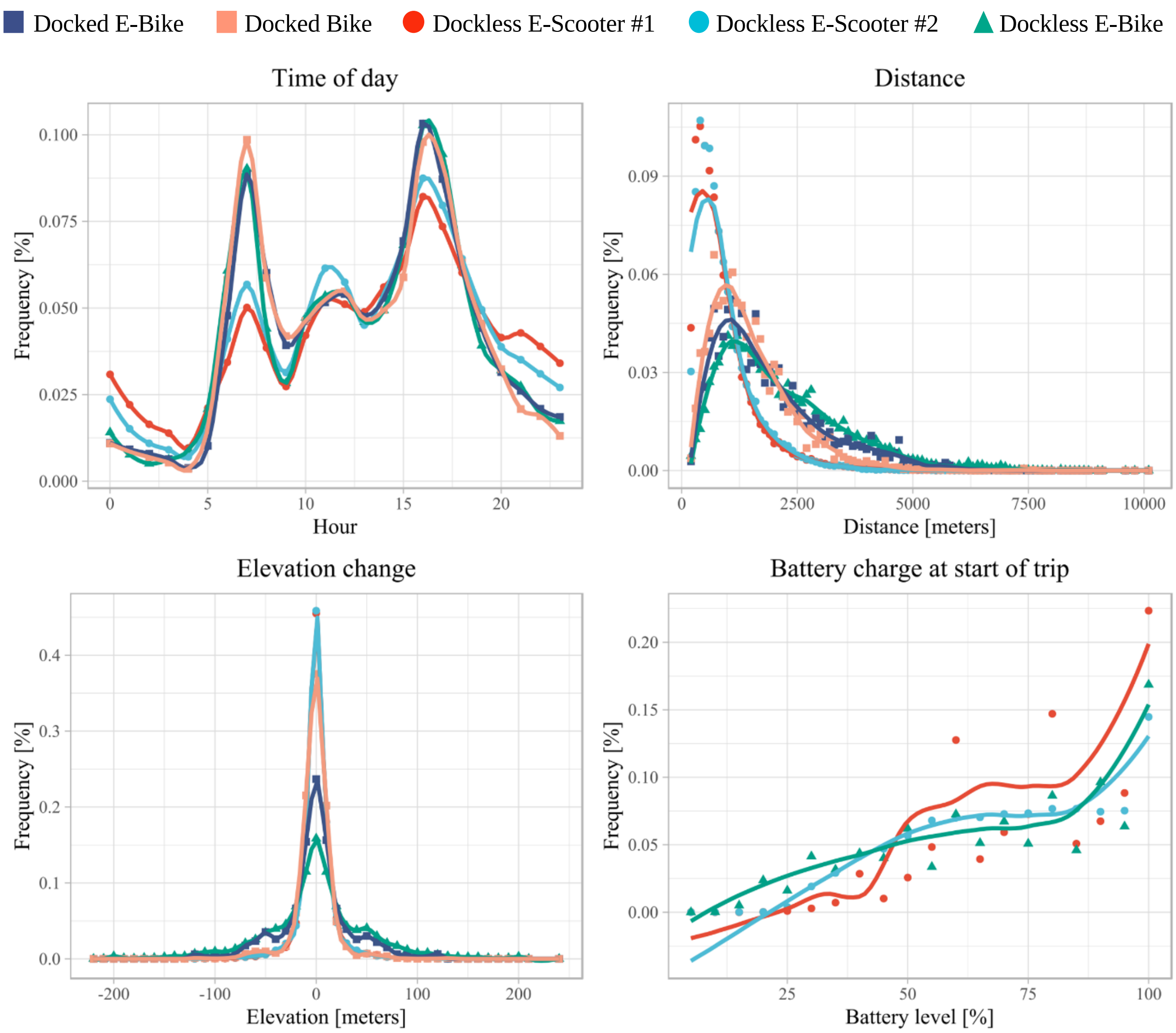
We separate the 168 895 micro-mobility trips into the corresponding modes and companies: 67 114 docked e-bike trips, 25 167 docked bike trips, 14 684 dockless e-bike trips, 31 920 dockless e-scooter trips (company #1) and 30 010 dockless e-scooter trips (company #2).

Figure 3 shows descriptive plots for the calculated trips by mode and company. Note that all curves are plotted relative to the total number of trips per category. 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 9 p.m. and 5 a.m.).

The plot by trip distance shows that e-scooters from both companies 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 (elevation at trip destination minus elevation at trip start) 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. Users are aware of the battery charge of available vehicles as it is displayed next to the price in the respective smartphone apps. Here, e-scooter company #2 exhibits further peaks at 60% and 80%, which we assume to be due to programming of battery information or charging cycles.

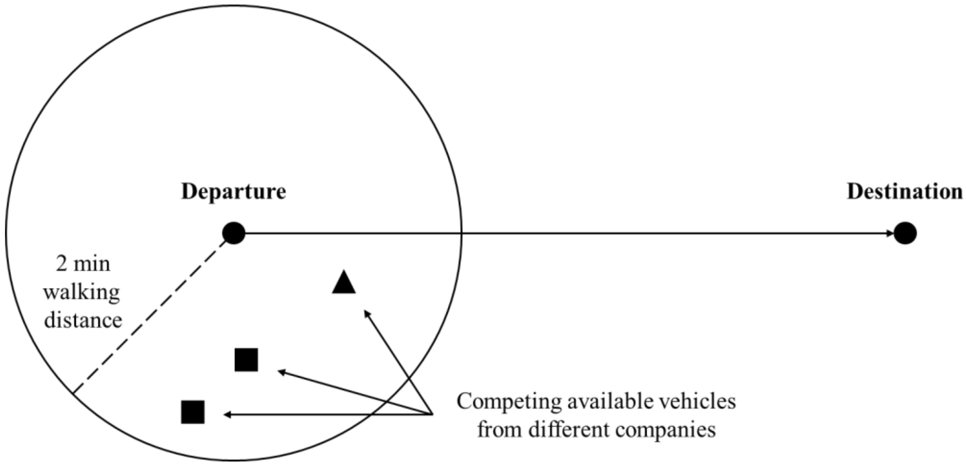
Figure 3 Descriptive statistics for trips conducted with different shared micro-mobility modes and companies in Zurich (smoothed lines).



2.4 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 two-minute walking distance (167m at 5 km/h walking speed) from the departure location and within two minutes to departure time (Figure 4). Note that micro-mobility 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.

Figure 4 Spatiotemporal window to identify competing vehicles.



Using this method, we were able to identify competing available vehicles for 139 559 trips (~82.6%). For each of those trips, we can thus define a choice situation, where one mode from a specific company was chosen while others were available. Each choice set is composed of a number (1 to 5) of available modes / companies and attributes that vary by mode / company. This includes the number of available vehicles ("vehicle density") within two-minute walking distance from the departure location, the battery charge (only available for dockless modes), prices and which mode / company 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	Mode / Company	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[6]	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 modes as they have simple pricing mechanisms. There is an unlocking cost of 1 CHF for both dockless e-scooter companies and a per-minute cost for all three companies (0.25 CHF for dockless e-bikes, 0.35 CHF for dockless e-scooter company #1 and 0.40 CHF for dockless e-scooter company #2). Price structures for docked modes are more complex as several different subscription schemes granting discounts of up to 100% for rides up to 30 minutes are available and commonly used[7]. As we do not have access to user-specific information, especially regarding the subscription schemes, price variables for these two modes are not included.

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-scooters 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

[6] 1 CHF = 1.03 USD at the time of writing (25 May 2020).

[7] In personal communication, the docked (e-)bike company stated that ~90% of all trips were conducted by subscribers to discount schemes allowing unlimited free rides up to a duration of 30 minutes. The subscription cost for such a scheme is 99 CHF / year. Many companies in Switzerland, however, include this subscription in employee benefits packages or offer them further discounted rates.

substantially higher for docked bikes (40%) and highest for docked e-bikes (64%).

Table 2 Number of vehicles, availabilities and choice probabilities for each mode and company.

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

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 company 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 have accounts in certain types of shared micro-mobility 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., 2021a). We specify the utility functions using the attributes presented in Table 1 and the following abbreviations. σ denotes the nested error component, which is only applied in the NECLM model.

Modes		Attributes	
ES1	Dockless E-Scooter Company #1	EL	Total elevation gain
ES2	Dockless E-Scooter Company #2	MO	Morning peak (binary)
ES	Dockless E-Scooter Companies (both)	NI	Night (binary)
DLEB	Dockless E-Bike	DE	Vehicle density
DEB	Docked E-Bike	DI	Distance
DBB	Docked Bike	BA	Battery charge
		PR	Price

Utility functions

$$U_{ES1} = ASC_{ES1} + \beta_{MO_{ES1}} * \mathrm{MO} + \beta_{NI_{ES1}} * \mathrm{NI} + \beta_{DE_{ES1}} * \mathrm{DE}_{\mathrm{ES1}} + \beta_{DI_{ES}} * \mathrm{DI} + \beta_{BA_{ES1}} * \mathrm{BA}_{\mathrm{ES1}} + \beta_{PR_{ES1}} * \mathrm{PR}_{\mathrm{ES1}}$$

$$U_{ES2} = ASC_{ES2} + \beta_{MO_{ES2}} * \mathrm{MO} + \beta_{NI_{ES2}} * \mathrm{NI} + \beta_{DE_{ES2}} * \mathrm{DE}_{\mathrm{ES2}} + \beta_{DI_{ES}} * \mathrm{DI} + \beta_{BA_{ES2}} * \mathrm{BA}_{\mathrm{ES2}} + \beta_{PR_{ES2}} * \mathrm{PR}_{\mathrm{ES2}}$$

$$U_{DLEB} = ASC_{DLEB} + \beta_{EL_{DLEB}} * \mathrm{EL} + \beta_{DE_{DLEB}} * \mathrm{DE}_{\mathrm{DLEB}} + \beta_{DI_{DLEB}} * \mathrm{DI} + \beta_{BA_{DLEB}} * \mathrm{BA}_{\mathrm{DLEB}} + \beta_{PR_{DLEB}} * \mathrm{PR}_{\mathrm{DLEB}}$$

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

$$U_{DEB} = \beta_{MO_{DEB}} * \mathrm{MO} + \beta_{NI_{DEB}} * \mathrm{NI} + \beta_{DE_{DEB}} * \mathrm{DE}_{\mathrm{DEB}} + \beta_{DI_{DEB}} * \log(\mathrm{DI}) + \sigma$$

2.5 RESULTS

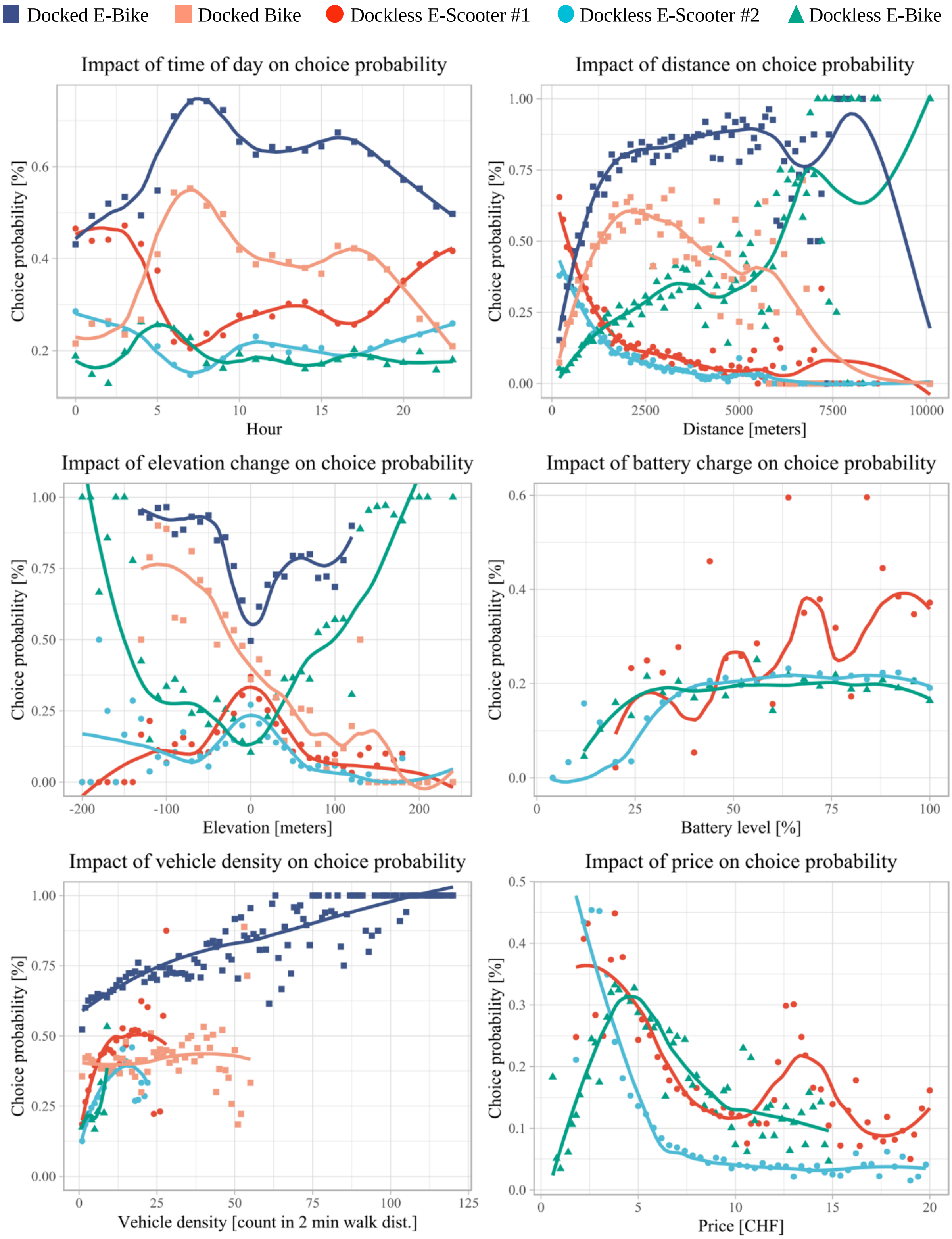
2.5.1 Bivariate relationships

Figure 5 shows plots of bivariate relationships between the choice probability (i.e., the average likelihood of choosing a particular mode over others) for each company 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.

Note the interesting difference between these plots and the descriptive plots (Figure 3) 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 3), 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 5), 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 3) thus only reveal shares of observed trips, the bivariate plots (Figure 5) 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.

Figure 5 Bivariate relationships between variables and choice probability (smoothed lines).



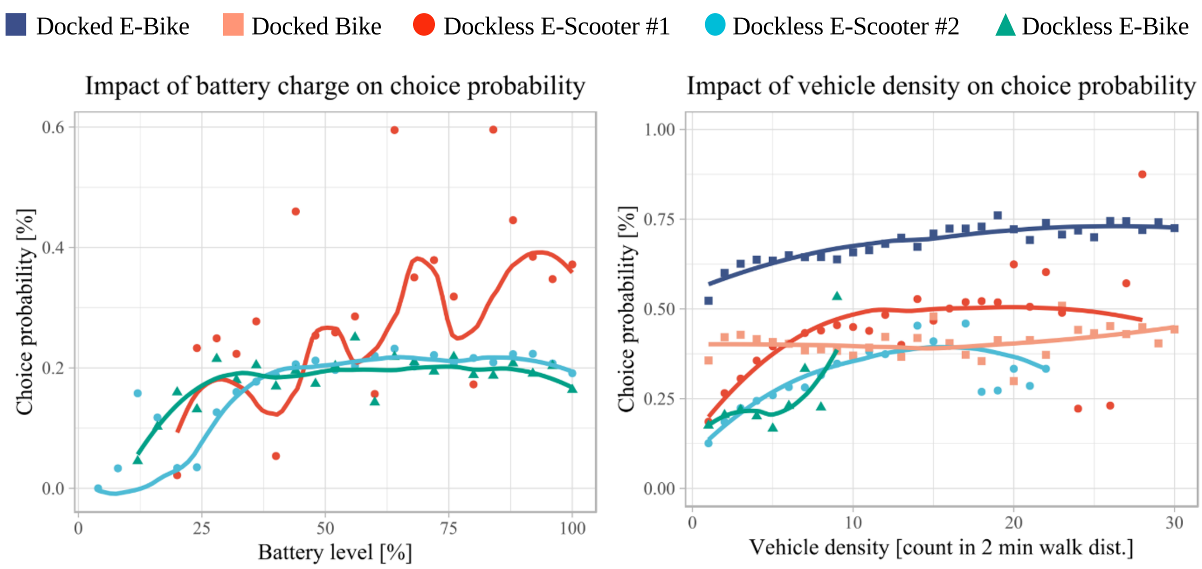
The plot by elevation shows that the choice probability for e-bikes (docked and dockless) is greater with increasing absolute elevation difference. In contrast, the choice probability for docked bikes peaks at the highest possible negative elevation difference (i.e., down-hill) and gradually decreases 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 services (dockless e-scooter company #2 and dockless e-bikes) 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 company #2 it appears to begin at ~50% battery charge. The difference can possibly 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 company #1 with several outliers. While there is no behavioural explanation for different effects between two dockless e-scooter companies 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 mode and company within two-minute walking distance of the trip departure location. The plot shows an increasing choice probability with increasing vehicle density for all modes and companies as one would expect. Both the rate (i.e., marginal utility gain) and the intercept differ by mode, however. Dockless modes 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 micro-mobility variants. We speculate that 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 micro-mobility mode, however, at this point this hypothesis remains speculation.

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 6) 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 two-minute walking distance (i.e., a circle of 167m radius at 5 km/h walking speed). The difference between the two dockless e-scooter companies could stem from different repositioning practices, for example, how many vehicles are placed and how closely they are placed to each other after recharging.

Figure 6 Evidence of decreasing marginal utility gains ("plateau effect") for battery charge and vehicle density (smoothed lines).



2.5.2 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[8] with a McFadden pseudo R^2 (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 R^2 of 0.35 (the nested error component σ is highly significant) indicating that indeed there appears to be the expected hierarchy in the decision-making process.

Table 3 displays the results for both models. All coefficients except for the battery charge for docked e-bikes are highly significant (though this is not surprising given the large sample size) 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. Micro-mobility 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 micro-mobility (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-scooters 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.

[8] McFadden (1979, p. 306) notes "Those unfamiliar with the ρ^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 ρ^2 represent an excellent fit."

Table 3 Estimation results.

			MNL		NECLM	
	Mode / Company	**Parameter**	**EST**	**SE**	**EST**	**SE**
Nest 1	Dockless E-Scooter Company #1	ASC	-1.94***	0.05	-5.01***	0.16
		Distance[1]	-0.10***	0.03	1.77***	0.11
		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
	Dockless E-Scooter Company #2	ASC	-0.67***	0.05	-3.53***	0.15
		Distance[1]	-0.10***	0.03	1.77***	0.11
		Price	-0.28***	0.01	-0.62***	0.02
		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
	Dockless E-Bike	ASC	-2.66***	0.05	-6.28***	0.16
		Distance	0.85***	0.02	2.97***	0.11
		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	Docked Bike	ASC	-0.42***	0.02	-0.50***	0.06
		Distance[2]	1.19***	0.03	6.81***	0.22
		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
	Docked E-Bike	Distance[2]	1.27***	0.03	6.91***	0.22
		Vehicle density	0.04***	0.00	0.09***	0.00
		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
		ρ^2		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

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 company #1 by 1% will decrease its choice probability -0.94 percentage points. Dockless e-scooter company #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 companies (+0.46 and +0.56 percentage points). Again, it becomes visible that both dockless e-scooter companies 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

2.6 DISCUSSION

Our analyses reveal that users prefer docked (e-)bikes during peak hours and dockless e-scooters during off-peak hours. Dockless e-bikes show a much less pronounced temporal pattern and are preferred for longer distances with larger elevation differences. The temporal patterns indicate that docked (e-)bikes are particularly 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 companies 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.

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 6). We term this fundamental relationship the "plateau effect" for micro-mobility 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. Policy makers 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.

2.7 CONCLUSIONS

This is the first study that comprehensively analyses usage, competition and mode choice for four different micro-mobility 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 micro-mobility data set 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 micro-mobility 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 suitable micro-mobility regulation and optimise their fleet deployment, respectively.

This study has some limitations that call for future work. First and foremost, our analysis only focuses on the impact of external and trip-level attributes on micro-mobility mode choice. This could be extended by including user-specific attributes (e.g., socio-demographics, vehicle ownership, micro-mobility service subscriptions), additional modes (e.g., public transport and walking) and destination-specific attributes (e.g., public transport availability, type of destination). Second, 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 company APIs. Therefore, similar analyses could be conducted in any other city to verify the external validity of our work. Third, transport network simulation is needed to fully understand the impact of micro-mobility on urban mobility and its sustainability. Our results on mode choice and underlying user preferences build the foundation for integrating micro-mobility in transport network simulations.

As the variety, availability and use of micro-mobility 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 micro-mobility 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 expand regulation from controlling for safety to controlling for quantity (i.e., vehicle licensing), address further regulatory issues (e.g., parking space allocation) as well as 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.

CRediT AUTHORSHIP CONTRIBUTION STATEMENT

Daniel J. Reck: Conceptualization, Methodology, Formal analysis, Investigation, Writing - original draft, Writing - review & editing. He Haitao: Conceptualization, Investigation, Writing - review & editing. Sergio Guidon: Conceptualization, Investigation. Kay W. Axhausen: Conceptualization, Investigation, Writing - review & editing.

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3. WHO USES SHARED MICRO-MOBILITY SERVICES? EMPIRICAL EVIDENCE FROM ZURICH, SWITZERLAND

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ABSTRACT

Shared micro-mobility services have rapidly gained popularity yet challenged city administrations to develop adequate policies while scientific insight is largely missing. From a transportation equity perspective, it is particularly important to understand user correlates, as they are the beneficiaries from public investment and reallocation of public space. This paper provides an up-to-date account of shared micro-mobility adoption and user characteristics in Zurich, Switzerland. Our results suggest that shared micro-mobility users tend to be young, university-educated males with full-time employment living in affluent households without children or cars. Shared e-scooter users, in particular, are younger, yet more representative of the general population in terms of education, full-time employment, income and gender than bike-sharing users. This suggests that shared e-scooters may contribute to transportation equity, yet their promotion should be handled with care as life-cycle emissions exceed those of bike-sharing and equity contributions might be skewed as many users are students.

3.1 INTRODUCTION

Shared micro-mobility services (e.g., shared e-scooters, shared bikes, shared e-bikes) have rapidly gained popularity in major cities around the world. Recently, NACTO (2020) reported 136M rides in 2019 in the US alone - a 62% increase from 2018, mostly due to the rise of shared e-scooters. Their sudden appearance and rapid expansion has challenged city administrations and raised many regulatory and planning questions: Where should they be allowed to be ridden and parked? Which infrastructure (e.g., bike lanes, recharging points, bike racks) should be adapted and newly created on redistributed public space? Should their usage be subsidized for certain social groups? To answer these questions, it is particularly important to understand who uses these new services and whether there are any equity[9] concerns (i.e., overrepresentation of certain social groups) as public investments and reallocations of public space will directly benefit them.

Scientific evidence on who uses shared micro-mobility services, however, strongly varies by mode. While there exists a substantial body of research on docked bike-sharing users (for recent reviews, see Eren and Uz, 2020, and Fishman, 2016), research on docked / dockless e-bike-sharing users is already much more limited (e.g., He et al., 2019, and Hess and Schubert, 2019) and research on shared e-scooter users is very scarce (e.g., Sanders et al., 2020). Shaheen and Cohen (2019, p. 11) recently concluded a report on shared micro-mobility user characteristics by stating: "more research is needed to understand the user demographics of dockless bikesharing and scooter sharing."

We contribute by conducting a large-scale survey among users of three shared micro-mobility services (docked bikes and e-bikes, dockless e-bikes, dockless e-scooters) in Zurich, Switzerland. We compare user characteristics in terms of person and household socio-demographics, travel priorities and access to shared micro-mobility services, and explain usage by estimating state of the art univariate and multivariate probit models.

This article is organized as follows. In Section 2, we review the literature on shared micro-mobility with a particular focus on user characteristics. In

[9] Equity is typically defined as the equivalence of input and output ratios (Adams, 1965; Cook and Hegtvedt, 1983; Walster et al., 1973). Equity concerns over public investment in transportation services arise when certain social groups (i.e., higher income) are overrepresented and thus benefit more from these investments in these services than others. For example, Banister (2018) has shown that higher income groups travel more regularly in airplanes and long-distance trains and thus overproportionately benefit from investments in airports and long-distance train networks.

Section 3, we introduce our data set. We then describe user characteristics of different shared micro-mobility services. In Section 5, we model shared micro-mobility usage and present the results. The last section discusses the results and concludes with recommendations for policy making and future work.

3.2 LITERATURE REVIEW

Research on shared micro-mobility can be broadly categorized into supply- and demand-side topics, of which the latter is more relevant to this paper. Demand-side research tends to focus on questions such as how and why specific services are used, and by whom. Demand-side research can be further categorized by types of factors that influence demand such as internal (e.g., user socio-demographics, values, attitudes), external (e.g., built environment and land use, geography, weather) and trip-related (e.g., distance, time of day, destinations). Internal factors are most relevant to the topic of this paper and thus the focus of this literature review.

We begin by reviewing the literature for station-based bike-sharing (which we refer to as "docked" in this paper to contrast the "dockless" alternatives) as it is the largest and most complete compared to other shared micro-mobility modes. Most studies identify a common set of four factors to influence bike-sharing usage: age, gender, income and education. Younger individuals are generally more likely to be users of docked bike-sharing schemes than older individuals (e.g., Buck et al., 2013; Chen et al., 2020; Eren and Uz, 2020; Fishman et al., 2013; Fishman et al., 2015; Fishman, 2016; Fuller et al., 2011; Ge et al., 2020; Shaheen et al., 2014; Shaheen and Cohen, 2019). Males join docked bike-sharing schemes more often than females (e.g., Bachand-Marleau et al., 2012; Chen et al., 2020; Fishman et al., 2013; Fishman et al., 2015; Fishman, 2016) though exceptions from this pattern have been reported (e.g., Buck et al., 2013) and it has been suggested that docked bike-sharing may indeed help to close the overall gender gap in cycling in North America (Goodyear, 2013). Income is mostly found to be positively correlated with docked bike-share usage (e.g., Bachand-Marleau et al., 2012; Eren and Uz, 2020; Fishman et al., 2013; Fishman et al., 2015; Fishman, 2016; Shaheen et al., 2014; Shaheen and Cohen, 2019) though the study conducted by Buck et al. (2013) in Washington, D.C., presents an exception here as well. This could be due to methodological differences, though, as income among bike-share users was found to be smaller than the mean, however larger than the median of the general population in Washington, D.C. Users of docked bike-sharing schemes often show higher levels of education (e.g., Eren and Uz, 2020; Fishman et al., 2013; Fishman et al., 2015; Fishman, 2016; Fuller et al., 2011; Shaheen et al., 2014; Shaheen and Cohen, 2019). Some authors have additionally reported that docked bike-sharing users show higher employment rates (i.e., full-time or part-time work) than the general population (Fishman et al., 2013; Fishman, 2016; Fuller et al., 2011).

Several other factors have been reported incidentally (and/or controversially) to influence docked bike-sharing usage such as private vehicle ownership (i.e., bike and car) and household structure. Chen et al. (2020) found a substantial share of car non-users in their sample of bike-sharing users while Shaheen et al. (2011) noted that car ownership was an attractive condition for the use of bike-sharing schemes (Eren and Uz, 2020). Buck et al. (2013) observed that households with bike-sharing users had fewer cars and bikes. Bachand-Marleau et al. (2012) found that those owning a bike were less frequent users of bike-sharing while Fishman et al. (2013) and Shaheen et al. (2011) concluded that bike-sharing users are more likely to own private bikes. Hyland et al. (2018) further found a negative impact of driving license ownership on bike-sharing usage while Bachand-Marleau et al. (2012) found that those with a driver's license had 1.5 times greater odds of using bike-sharing. Last but not least, Shaheen and Cohen (2019) found a higher share of childless households among docked bike-sharing users.

Up to date, only few academic studies have investigated user characteristics of shared micro-mobility schemes other than docked bike-sharing. Chen et al. (2020) compared station-based and free-floating bike-sharing user structures in Hangzhou, China. They concluded that user structures are indeed similar. However, different factors influence the usage intensity of both modes. He et al. (2019) analyzed users of a shared e-bike system in Utah. They found that middle-aged population groups use e-bike-sharing frequently in addition to the usually reported younger population groups. Finally, Hess and Schubert (2019) analyzed socio-demographics of cargo e-bike-sharing in Switzerland. They found that users are predominantly young, cycling males.

To our knowledge, only one peer-reviewed academic study (Sanders et al., 2020) analyzed user characteristics of shared dockless e-scooters[10]. They

[10] There have been studies analysing the intent to use e-scooters (e.g., Eccarius and Lu, 2020), however, these were disregarded in our literature review as we focus on correlates of real users as they are not subject to hypothetical bias (Hensher, 2010).

conducted a survey in Tempe, AZ, and found that e-scooter users were mostly young (25-34) males and that income varied with riding patterns (i.e., most frequent riders had an annual household income between 50 000 USD and 99 000 USD). The latest edition of NACTO's report on shared micro-mobility (NACTO, 2020) also offers first insights into user characteristics. Surveys conducted in five US cities suggest that users are younger than the general population and predominantly male. Income distributions appear to vary by city, twice matching area median income and once substantially exceeding it.

The gap in the academic literature on rigorous identification of socio-demographic characteristics for users of shared micro-mobility schemes other than docked bike-sharing is apparent. In particular, very little is known about users of relatively new schemes (i.e., e-bike-sharing, e-scooter-sharing). In addition, the factors influencing real usage (as opposed to usage intention) across different schemes in a single location have not been analyzed yet. This is, however, important as external factors such as weather, geography and built environment influence demand substantially (e.g., Wang et al., 2018) and thus complicate cross-regional comparisons (c.f. the effect of income on dockless e-scooter usage as reported by NACTO, 2020). Closing this gap is urgent as policy makers need to understand who benefits from these schemes to develop suitable and equitable regulation and direct infrastructure investment and reallocations of public space. Researchers will benefit from sound evidence on user characteristics to improve multimodal choice models that are needed for transportation simulations and forecasts.

3.3 DATA

3.3.1 Location

We collect data on users of shared micro-mobility services in Zurich, Switzerland. Zurich is the largest Swiss city with 434K inhabitants (1.5M in the metropolitan area) and one of Switzerland's economic centers. Several shared micro-mobility providers operate in Zurich, making it a suitable place to analyze their users. The most established one is Publibike, which offers docked bikes and e-bikes at ~160 stations in Zurich. Bond Mobility 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 and Voi.

3.3.2 Survey

We designed an online survey as the principal data source for the subsequent analyses. The survey (see Appendix A.2 for German and Appendix A.3 for English) includes questions structured into the following three blocks:

- Person-specific socio-demographic questions (e.g., year of birth, gender, educational attainment, current occupation)
- Household-specific socio-demographic questions (e.g., number of adults and children, monthly income, vehicle ownership)
- Person-specific mobility questions (e.g., public season ticket ownership, travel priorities, knowledge of and accounts in shared (micro-) mobility schemes, frequency of use, access to shared micro-mobility services at home and work).

All questions and answer categories were formulated to be equal to the latest available Swiss microcensus[11] to enable direct comparison (see Section 3.3.4. below).

3.3.3 Recruitment

17 500 randomly selected inhabitants of Zurich municipality of age 18 to 65 were invited to participate in this study. Invitations containing a QR code as well as link to the online survey were sent by post by the cantonal statistical office as part of two larger studies. Respondents of study A were offered a reward of 50 CHF[12] for participating in two surveys and two months of smartphone tracking. Respondents of study B were offered a reward of 90 CHF for participating in two surveys and three months of smartphone tracking. All participants consented to data collection and data processing methods in compliance with the EU General Data Protection Regulation. Here, we report on the results and participation rates of the first survey only, which was identical for both study groups.

[11] Documentation in English can be found here:
https://www.are.admin.ch/are/en/home/mobility/data/mtmc.html.
Questionnaires are available in German:
(https://www.bfs.admin.ch/bfs/de/home/statistiken/mobilitaet-verkehr/erhebungen/mzmv.assetdetail.5606052.html)
and French: (https://www.bfs.admin.ch/bfs/fr/home/statistiques/mobilite-transports/enquetes/mzmv.assetdetail.5606053.html).
[12] 1 CHF = 1.09 USD at the time of writing (22 September 2020).

A total of 1 958 (11%) people returned the survey between July and August 2020. No follow up measures were conducted to maximize the sample size (i.e., every respondent only received one invitation to participate in the study). Only completed questionnaires were considered for the analysis. Further, questionnaires missing information such as income or travel priorities were excluded from the analyses. In total, 1 454 (8%) valid questionnaires remained for analysis.

3.3.4 Representativeness

We compare socio-demographic characteristics between survey respondents and census information for Zurich municipality to investigate the overall representativeness of our survey given a potential self-selection bias. The latest available censuses are the 2015 microcensus ("Mikrozensus Mobilität und Verkehr", MZMV), which contains all relevant socio-demographic and mobility-related information, and the more current yet limited in scope (i.e., no mobility-related information) 2018 census ("Strukturdatenerhebung", SE).

Table 5 shows the resulting comparison. Respondents of our survey were slightly younger (mean: 38 years) than the respondents of the censuses (2015: 42 years, 2018: 41 years) and overrepresent the age groups between 21-30 and 31-40 years. Our sample further includes slightly fewer females (47%) than the censuses (2015: 50%, 2018: 51%). The three surveys (2015, 2018, 2020) show two general societal trends: an increasing share of inhabitants holding a university degree (2015: 49%, 2018: 58%, 2020: 73%) and increasing full-time employment (2015: 63%, 2018: 68%, 2020: 80%). In line, mean monthly household income is found to be increasing from ~9 000 CHF to ~10 000 CHF. The household structure appears to be shifting to an increasing share of households with zero children (2015: 62%, 2018: 70%, 2020: 74%) and an increasing share of single or dual adult households (2015: 71%, 2018: 84%, 2020: 87%).

Table 5 Comparison of socio-demographic characteristics between survey respondents and Zurich municipality censuses.

	This survey	Census (SE)	Census (MZMV)
Year	2020	2018	2015
N (Zurich municipality only)	1 454	7 808	809
Filtered for age groups	18-65	18-65	18-65
Person-specific attributes			
Age			
18-20	1	3	2
21-30	27	20	16
31-40	37	31	28
41-50	21	22	25
51-60	10	18	21
61-65	4	7	8
Female	47	50	51
Education (university degree)	73	58	49
Full-time employed	80	68	63
PT season ticket ownership			
National, 100% off	19	n/a	16
Local (Zurich), 100% off	37	n/a	43
Household-specific attributes			
Monthly income			
4 000 CHF and below	18	n/a	11
4 001 CHF - 8 000 CHF	21	n/a	35
8 001 CHF - 12 000 CHF	22	n/a	26
12 001 CHF - 16 000 CHF	26	n/a	14
16 000 CHF and above	14	n/a	14
Children			
0	74	70	62
1	12	14	17
2 and above	15	15	20
Adults			
1	27	28	15
2	60	56	56
3 and above	13	15	29
Cars			
0	50	n/a	45
1	42	n/a	43
2 and above	8	n/a	11
Bikes			
0	17	n/a	19
1	20	n/a	25
2 and above	63	n/a	56
E-bikes			
0	86	n/a	95
1	10	n/a	4
2 and above	3	n/a	1

Swiss public transportation season tickets mainly fall into two categories: local and national. Local season ticket holders are slightly underrepresented in our survey (37% vs 43% in 2015) while national season ticket holders are slightly overrepresented (19% vs 16% in 2015). Households in our survey owned slightly fewer cars and slightly more bikes and e-bikes compared to the 2015 census.

3.4 DESCRIPTIVE ANALYSIS OF USER CHARACTERISTICS OF SHARED MICRO-MOBILITY SERVICES

We proceed by comparing characteristics of users of different micro-mobility schemes descriptively, before modelling usage in the subsequent section.

3.4.1 Account holders and usage frequency

We begin with an overview of account holders and usage frequencies of shared micro-mobility schemes. Dockless e-scooter schemes had most account holders in our sample (28%), while docked (e-) bikes (16%) and dockless e-bikes (9%) were substantially less popular. Interestingly, while e-scooter ownership is (still?) uncommon (3%), e-bike ownership is substantially more common (14%). Most account holders of dockless e-scooter schemes (39%) only had an account with one company, while 23% had accounts with two companies, 18% with three companies, and 20% with all four companies. The largest shared e-scooter company (in terms of account holders) unites 78% of all account holders, while the smallest company only unites 27% of all account holders.

While the terms 'member' and 'user' are often used interchangeably, their connotations are different and thus should be distinguished. The term 'member' has a static connotation and comprises both active and inactive or 'dormant' users. In this study, we hence use the term 'account holder' instead of 'member'. The term 'user' on the other hand has an active connotation that is linked to actual usage. For the purpose of this study, we define users as respondents who use a shared micro-mobility scheme at least 'several times per month'. Table 6 differentiates account holders with shared micro-mobility services by usage frequency to illustrate and quantify this difference. We find that account holders with docked (e-) bike schemes are most active (92%) while account holders with dockless e-bike schemes (53%) and dockless e-scooter schemes (44%) and are substantially less active. In other words, a substantial share of account holders in shared micro-mobility schemes is inactive or dormant. In line with our research question, we proceed our analysis with the subsample of active users only.

Table 6 Account holders or users? Shared micro-mobility account holders by usage frequency.

Usage frequency	Shared dockless e-scooter account holders	Shared docked (e-) bike account holders	Shared dockless e-bike account holders
(almost) daily	8	105	21
several times each week	36	55	21
several times each month	134	47	31
less often / never	219	18	64
(not answered)	12	1	1
n	409	226	138
Share of "active users" (at least several times each month)	44%	92%	53%

3.4.2 Socio-demographics

Table 7 shows person-specific and household-specific attributes and corresponding values of the three shared micro-mobility user groups (shared dockless e-scooters, shared docked (e-) bikes, shared dockless e-bikes). The last column shows the values for all respondents of our survey. Values in parentheses show differences in percentage points between each group and all respondents.

The side-by-side comparison of the different groups reveals several commonalities. Shared micro-mobility users in our sample tend to be young, university-educated males with full-time employment living in affluent households without children or cars. Exceptions from this general pattern reveal the differences between the groups. Users of shared dockless e-scooter schemes tend to be younger (mean: 33 years) than users of shared docked (e-) bike and dockless e-bike schemes (means: 36 and 39 years, respectively). They exhibit the "smallest" (yet substantial) gender disparity of all shared micro-mobility modes (32% females vs 29% and 18% for docked (e-) bikes and dockless e-bikes, respectively) and show a lower university education level (71%) and full-time employment level (79%) than all other shared micro-mobility modes (81% and 83% for docked (e-) bikes, 78% and 85% for dockless e-bikes). Their average monthly household income (10,200 CHF) is substantially lower than that of users of both other shared micro-mobility modes (11 200 CHF for dockless e-bikes, 11 000 CHF for docked (e-) bikes). Indeed, in these three socio-demographic categories (university education, full-time employment and household income), users of shared dockless e-scooter schemes are much more similar to the overall sample than to users of both bike-sharing schemes. Household structures differ mainly in that substantially more dockless e-scooter users live in households without children (87%) than the overall sample (74%) and that more households are single adult households than in the overall sample. These findings correspond with the slightly larger share of students among users of shared e-scooter schemes (15%) than in the overall sample (14%) or indeed any other shared micro-mobility scheme, as students in Zurich typically live alone or in shared flats, have lower (own) income, lower (completed) levels of education and are not (yet) full-time employed.

Users of the shared dockless e-bike schemes, in contrary, exhibit particularly strong differences in socio-demographics. 82% of all users of the shared dockless e-bike scheme in our sample are males, which compares to 53% in the overall sample. They are particularly well educated (78% hold a university degree) in comparison to the overall sample (73%). They also show the highest rate of full-time employment (85%) which compares to 80% in the overall sample. In line, their mean monthly household income is also substantially higher (11 200 CHF) than that of households in the overall sample (10,300 CHF).

Users of the shared docked (e-) bike scheme fall well within the general pattern in terms of age, gender, education and income. They are younger (mean: 36 years) than the overall population (mean: 38 years) but not as young as shared e-scooter users (mean: 33 years). They are predominantly male (71%, +18 pp. in comparison to the overall sample) and live in more affluent households (mean monthly income: 11 000 CHF), yet this pattern is not as strong as for shared dockless e-bike users (82% and 11 400 CHF, respectively). Two characteristics, however, distinguish them from other shared micro-mobility users. First, they have substantially less access to private cars (44%) in comparison to shared e-scooter users (50%), dockless e-bike users (52%) and the overall sample (54%). Second, they hold substantially more frequently a countrywide public transportation season ticket (29%) in comparison to other shared micro-mobility users and the overall sample (19%).

Table 7 Descriptive comparison of socio-demographic characteristics of users of different shared mobility services (in percentages of subsamples; parentheses indicate differences to total sample in percentage points).

	Shared dockless e-scooter users		Shared docked (e-) bike users		Shared dockless e-bike users		Total
(Sub-) Sample size							
N	178		207		73		1 454
% of total	12		14		5		100
Person-specific attributes							
Age							
18-20	3	(+2)	1	(-)	0	(-1)	1
21-30	42	(+15)	30	(+3)	16	(-11)	27
31-40	38	(+1)	41	(+4)	42	(+5)	37
41-50	13	(-8)	18	(-3)	26	(+5)	21
51-60	3	(-7)	8	(-2)	12	(+2)	10
61-65	1	(-3)	2	(-2)	3	(-1)	4
Female	32	(-15)	29	(-18)	18	(-29)	47
Driver's license ownership	94	(-)	96	(+2)	100	(+6)	94
Access to car (frequent / always)	50	(-4)	44	(-10)	52	(-2)	54
Education (university degree)	71	(-2)	81	(+8)	78	(+5)	73
Employment							
In training	15	(+1)	13	(-1)	10	(-4)	14
Full-time employed	79	(-1)	83	(+3)	85	(+5)	80
PT season ticket ownership							
National, 100% off	28	(+9)	29	(+10)	32	(+7)	19
Local (Zurich), 100% off	39	(+2)	37	(-)	34	(-3)	37
Travel priority: environment							
Not important	8	(+5)	3	(-)	7	(+4)	3
Rather unimportant	20	(+5)	20	(+5)	16	(+1)	15
Rather important	35	(+1)	29	(-7)	27	(-9)	36
Important	37	(-9)	48	(+2)	49	(+3)	46
Travel priority: time							
Not important	0	(-1)	1	(-)	0	(-1)	1
Rather unimportant	2	(-6)	6	(-2)	8	(-)	8
Rather important	26	(-4)	32	(+2)	26	(-4)	30
Important	71	(+9)	61	(-1)	66	(+4)	62
Travel priority: flexibility							
Not important	0	(-1)	1	(-)	0	(-1)	1
Rather unimportant	3	(-4)	8	(+1)	4	(-3)	7
Rather important	24	(-4)	29	(+1)	27	(-1)	28
Important	74	(+10)	62	(-2)	68	(+4)	64
Household-specific attributes							
Monthly income							
4 000 CHF and below	16	(-2)	18	(-)	10	(-8)	18
4 001 CHF - 8 000 CHF	22	(+1)	22	(+1)	23	(+2)	21
8 001 CHF - 12 000 CHF	25	(+3)	25	(+3)	27	(+5)	22
12 001 CHF - 16 000 CHF	26	(-)	25	(-1)	27	(+1)	26
16 000 CHF and above	11	(-3)	11	(-3)	12	(-2)	14

	Shared dockless e-scooter users		Shared docked (e-) bike users		Shared dockless e-bike users		Total
Children							
0	87	(+13)	81	(+7)	75	(+1)	74
1	6	(-6)	6	(-6)	11	(-1)	12
2 and above	7	(-8)	14	(-1)	14	(-1)	15
Adults							
1	32	(+5)	28	(+1)	22	(-5)	27
2	55	(-5)	59	(-1)	66	(+6)	60
3 and above	13	(-)	14	(+1)	12	(-1)	13
Cars							
0	56	(+6)	58	(+8)	55	(+5)	50
1	36	(-6)	35	(-7)	36	(-6)	42
2 and above	8	(-)	7	(-1)	10	(+2)	8
Bikes							
0	24	(+7)	10	(-7)	19	(+2)	17
1	24	(+4)	20	(-)	25	(+5)	20
2 and above	52	(-11)	70	(+7)	56	(-7)	63
E-bikes							
0	88	(+2)	86	(-)	66	(-20)	86
1	8	(-2)	10	(-)	19	(+9)	10
2 and above	3	(-)	5	(+2)	15	(+12)	3
E-scooters							
0	89	(-8)	97	(-)	100	(+3)	97
1	8	(+5)	2	(-1)	0	(-3)	3
2 and above	2	(+2)	0	(-)	0	(-)	0
Shared micro-mobility access[1]							
Bike-share at home	82	(+5)	90	(+13)	90	(+13)	77
Bike-share at work	58	(-)	68	(+10)	71	(+13)	58
Shared e-scooters at home	90	(+10)	85	(+5)	83	(+3)	80
Shared e-scooters at work	65	(+9)	61	(+5)	67	(+11)	56

[1] Read this section as follows. Example for line "Bike-share at home": "82% of all users of shared dockless e-scooters stated to have access to bike-share at home. This is 5 percentage points more than in the overall sample."

Finally, we note that vehicle ownership appears to coincide with usage, i.e. respondents who own e-scooters/e-bikes are more likely to use shared e-scooters/e-bikes as well.

3.4.3 Travel priorities

We asked the respondents to assess the importance of travel priorities such as protecting the environment, travel time and flexibility on a four-point scale from not important to important. Users of micro-mobility services, on average, assess travel time and flexibility to be more important and protecting the environment to be less important than the overall sample. Shared e-scooter users, in particular, responded substantially less often that protecting the environment was important to them (-9 pp. in comparison to the overall sample) while they responded substantially more often that travel time (+9 pp.) and flexibility (+10 pp.) was important to them.

3.4.4 Shared micro-mobility access

We further asked the respondents to evaluate their access to shared micro-mobility services at home and at work. Most respondents confirmed that shared e-scooters and shared (e-) bikes were available at home which came at no surprise as only residents of Zurich municipality were invited to participate in the survey. Within Zurich municipality, only few areas are excluded from most operator's zones. At work, access to shared micro-mobility is less common, though. This difference can be explained with working locations. While all 1 454 respondents live in Zurich municipality, only 1 060 stated that they also work in Zurich municipality. Within each shared micro-mobility user group, respondents naturally evaluated access to shared micro-mobility services higher than the overall sample., i.e. 90% of shared e-scooter users reported that shared e-scooters were available at home (+10 pp. in comparison to the overall sample).

3.5 MODELLING SHARED MICRO-MOBILITY USAGE

In the previous section, we explored characteristics of shared micro-mobility users descriptively. We proceed by modelling usage leveraging the previously discovered relationships to explore their relative size and significance.

3.5.1 Methodology

The dependent variable to model, shared micro-mobility usage, is binary here (i.e., each respondent qualifies as an active user or not as outlined in Section 3.4). We thus model usage using probit models (Greene, 2012). As usage of different schemes, i.e. dockless e-scooters and dockless e-bikes, might be correlated, we further model usage jointly using a multivariate probit model (MVP). The MVP approach allows error terms between individual choices to be correlated and is commonly used in transportation research to model vehicle

/ public transport season ticket ownership, among others (e.g., Becker et al., 2017; Choo and Mokhtarian, 2008; Yamamoto, 2009).

Our univariate probit models (UVP) individually, and jointly as the multivariate probit model (MVP) for i mobility schemes, have the following form

$$Y_i^* = \beta_i X + \varepsilon_i, i = 1,2,3,4,5 \tag{1}$$

where Y_i^* is an unobserved vector representing the latent utility or propensity to being user of each mobility scheme i, β_i is a vector representing the coefficients to be estimated for each mobility scheme i, x is a vector representing the observed characteristics believed to be relevant to the decision (see previous section), and ε_i is the error term for each mobility scheme. The variance-covariance matrix of the error term is

$$\Sigma = \begin{bmatrix} 1 & \cdots & \rho_{1,5} \\ \vdots & \ddots & \vdots \\ & \cdots & 1 \end{bmatrix}. \tag{2}$$

The observed binary variables $Y_i = 1$ if $Y_i^* > 0$, 0 otherwise. The correlations in Σ are informative as positive correlations indicate mobility schemes to be complements, and negative correlations indicate mobility schemes to be substitutes. They further indicate whether decisions are indeed related and thus require joint modelling.

We estimate all parameters by maximum simulated likelihood (Cappellari and Jenkins, 2006) which have been shown to be consistent, asymptotically normal and efficient if the number of draws is chosen greater than the square root of the sample size (Cappellari and Jenkins; 2003; Train, 2003). Here, we use 100 draws, which is substantially higher than $\sqrt{1454} \approx 38$. We use Stata 15 and the package mvprobit (Cappellari and Jenkins, 2003) for model estimation with robust standard errors.

3.5.2 Results

Table 8 summarizes the results of the three univariate probit models (UVP) for each shared micro-mobility scheme and the joint multivariate probit model (MVP). All coefficients were estimated for each model, but we only discuss the significant ones in the following paragraphs.

Table 8 Estimation results for univariate probit (UVP) models and multivariate probit (MVP) model.

	Shared dockless e-scooter usage		**Shared docked (e-) bike usage**		**Shared dockless e-bike usage**	
	UVP	MVP	UVP	MVP	UVP	MVP
Constant	-1.20**	-1.15*	-1.36**	-1.34**	-3.05***	-6.98
Person-specific attributes						
Age	-0.03***	-0.03***	-0.01**	-0.01**	0.00	0.00
Female	-0.46***	-0.46***	-0.50***	-0.51***	-0.71***	-0.72***
Driver's license	0.08	0.07	0.22	0.22	0.23	0.23
Access to car (frequent / always)	-0.06	-0.05	-0.32*	-0.31*	-0.12	-0.05
Education (university)	-0.11	-0.12	0.06	0.04	0.02	0.02
Employment (fulltime)	-0.05	-0.04	0.17	0.17	0.26	0.25
PT season ticket (country)	0.37**	0.39**	0.38**	0.39**	0.39*	0.33*
PT season ticket (local)	0.13	0.13	0.17	0.16	0.12	0.08
Travel priority: environment	-0.16**	-0.16**	-0.04	-0.04	-0.05	-0.07
Travel priority: time	0.22*	0.22**	0.00	-0.01	0.03	-0.01
Travel priority: flexibility	0.25**	0.25**	-0.03	-0.02	0.17	0.22
Household-specific attributes						
Income	0.02	0.01	0.02	0.02	0.00	0.01
# Children	-0.26	-0.23	-0.31**	-0.31**	-0.06	-0.10
# Adults	-0.12	-0.12	-0.09	-0.09	0.10	0.10
# Cars	-0.04	-0.05	0.10	0.09	-0.08	-0.15
# Bikes	-0.07*	-0.08*	0.10**	0.10**	-0.03	-0.01
# E-bikes	0.13	0.14	0.12	0.15	0.58***	0.61***
# E-scooters	0.49***	0.49***	-0.06	-0.07	0.02	0.02
Shared micro-mobility access						
Bike-share at home	0.23	0.23	0.75***	0.76***	0.85**	0.77**
Bike-share at work	-0.37*	-0.36*	0.40**	0.40**	0.21	0.21
Shared e-scooters at home	0.45**	0.44**	-0.15	-0.15	-0.31	-0.24
Shared e-scooters at work	0.44**	0.44**	-0.28	-0.29	0.06	0.04
N	1 454	1 454†	1 454	1 454†	1 454	1 454†
Log likelihood final	-450	-1 143†	-517	-1 143†	-234	-1 143†
Log likelihood null	-540	-1 208†	-595	-1 208†	-283	-1 208†
McFadden R^2	0.168	0.054†	0.130	0.054†	0.173	0.054†

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

† Estimated jointly (MVP).

Though there is no established measure for the goodness of fit of such models, McFadden's R^2 calculated as

$$R^2 = 1 - \frac{\log[\mathrm{L}(\beta)]}{\log[\mathrm{L}_0]}, \tag{3}$$

where $\mathrm{L}(\beta)$ is the value of the unconstrained log likelihood function and L_0 is the value of the log likelihood function where all regression coefficients are zero, is commonly used (Becker et al., 2017; Choo and Mokhtarian, 2008; Lansink et al., 2003).

McFadden's R^2 of the final UVP models range between 0.130 (shared docked (e-) bike usage) and 0.173 (shared dockless e-bike usage) which is well within the range of the goodness of fit of previously reported models (Becker et al., 2017; Choo and Mokhtarian, 2008). Table 9 shows that the correlations between all the error terms of the individual equations are positive and significant, confirming that an MVP is efficient to use to estimate usage jointly. Interestingly, McFadden's R^2 is substantially lower for the MVP model (0.054) than for the UVP models indicating that it is substantially more difficult to explain joint usage of shared micro-mobility modes than to explain usage / non-usage separately. Overall, both the significance levels and the size of the coefficients between the UVP models and the MVP model are very similar and we thus continue to report the results of the MVP model.

Table 9 Correlations in the error terms of the individual equations of the multivariate probit model.

	Shared dockless e-scooter usage	Shared docked (e-) bike usage	Share dockless e-bike usage
Shared dockless e-scooter usage	n/a	0.37***	0.48***
Shared docked (e-) bike usage	n/a	n/a	0.63***
Shared dockless e-bike usage	n/a	n/a	n/a

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Out of all variables tested, gender and the national public transportation season ticket ownership are the only two universally significant and highly substantial binary variables to influence shared micro-mobility usage. Females are consistently and substantially less likely than men to become users of shared micro-mobility schemes, least so for shared dockless e-bikes. Ownership of a national public transportation season ticket consistently and positively influences usage of all shared micro-mobility modes. Furthermore, private vehicle ownership correlates with shared vehicle usage, i.e. respondents owning e-scooters/e-bikes are also more likely to use shared e-scooters/e-bikes. Non-surprisingly, access to shared (e-) bikes and e-scooters also correlates with shared mobility usage within each respective scheme.

Usage of shared e-scooter schemes is further significantly and negatively influenced by age (most substantially of all analyzed mobility services), travel priorities in favor of flexibility and time, and against the environment. Usage of shared docked (e-) bike schemes, in turn, is negatively influenced by age (though not as much as for shared e-scooters), frequent access to cars and the number of children in the household.

3.6 CONCLUDING DISCUSSION

How do our results compare with previous literature on shared micro-mobility users, and what can we learn from them?

Previous literature on docked bike-sharing largely agrees that users tend to be younger and more highly educated than the general population. They are further typically found to be predominantly male and to live in households that are more affluent. Anecdotal evidence points towards a positive correlation with full-time employment and a negative correlation with household size (in particular number of children), while it is disputed whether vehicle ownership (cars, bikes) has a positive or a negative correlation with docked bike-sharing usage. The small body of literature on shared, dockless e-bikes suggests their users could be similar to docked bike-sharing and potentially include a higher share of older age groups. First evidence suggests that users of shared e-scooter schemes are particularly young and predominantly male.

We find that users of shared micro-mobility services in Zurich indeed also tend to be young, university-educated males with full-time employment living in affluent households without children or cars (see Table 10 for a summary of the main results).

Table 10 Key differences between shared micro-mobility user groups and overall Zurich population.

	Shared dockless e-scooter users	Shared docked (e-) bike users	Share dockless e-bike users	Zurich (SE 2018)
Age (mean)	33 yrs	36 yrs	39 yrs	41 yrs
Gender (female)	32 %	29 %	18 %	50 %
University degree (share)	71 %	81 %	78 %	58 %
Full-time employment (share)	79 %	83 %	85 %	68 %
Household income (mean)	10 200 CHF	11 000 CHF	11 200 CHF	9 300 CHF †
Households without children (share)	87 %	81 %	75 %	70 %
Households without cars (share)	56 %	58 %	55 %	45 % †

† Source: MZMV 2015 (not available in SE 2018)

We further find that vehicle ownership correlates with usage, i.e. those who own e-scooters/e-bikes are more likely to use shared e-scooters/e-bikes as well. For bike-sharing, this confirms previous findings of Fishman et al. (2013) and Shaheen et al. (2011) and differs from previous findings of Bachand-Marleau et al. (2012) and Buck et al. (2013). We are the first to extend these findings from bike-sharing to e-bikes and e-scooters. Owners of national public transportation season tickets are further consistently more likely to use shared micro-mobility.

Exceptions from these general patterns illustrate that previous findings for one mode cannot always be generalized to others. While users of shared e-scooter schemes are particularly young and males are still in the majority, more females use them than shared bikes. In terms of educational attainment, full-time employment and mean household income, shared e-scooter users are also more similar to the general population than to their bike-sharing peers. This could, however, be due to a higher share of students among shared e-scooter users, who have lower (own) income, lower (completed) levels of education and who are not (yet) full-time employed. Equity contributions, in particular in comparison to shared e-bike users, could hence be skewed and short-lived. Shared e-scooter users being more representative of the overall population than bike-sharing users further appears counter-intuitive with respect to income as shared e-scooters in Zurich were the most expensive shared micro-mobility mode at the time the survey was conducted: a ten-minute journey with a shared e-scooter, for example, cost between 4 - 5 CHF (depending on the operator), which compared to 2.9 CHF for docked bike-sharing, 4.9 CHF for docked e-bike-sharing and 2.5 CHF for dockless e-bike-sharing. It suggests, however, that disposable income might be different among the different shared micro-mobility groups (i.e., students might have a higher share of disposable income than other social groups) or that price might be less important for shared e-scooter mode choice than for other modes.

Our findings on the socio-demographic background of users of shared micro-mobility services relate well to the results of broader research on technology adoption. The 'innovation diffusion' model by Rogers (1995) is commonly employed to study socio-demographic profiles in five consecutive categories of technology adopters (innovators, early adopters, early majority, late majority, laggards). Previous studies in a variety of sectors conclude with very similar results to ours, i.e. innovators and early adopters of new technologies tend to be young, highly educated, relatively wealthy, male individuals (e.g., Black et al., 2001; Li et al., 2008; Lockett and Littler, 1997; Polatoglu and Ekin, 2001; Reinen and Plomp, 1993; Sulaiman et al., 2007; Morris and Venkatesh, 2000; Wood and Li, 2005), though there is some evidence that the gender gap may be narrowing at least in some contexts (e.g., DeBaillon and Rockwell, 2005, Li et al., 2008; Rainer et al., 2003; Ray et al., 1999).

Having identified these similarities in findings with previous studies, can we also learn from their suggestions to make transport (i.e., shared micro-mobility in this particular case) more equitable? At its core, transport provides accessibility, and equity in accessibility has been a long established priority for transport policy. The efficacy of means to achieve equitable accessibility, however, is highly context-dependent and includes additional considerations such as costs and sustainability. In other words, while increasing the inclusiveness (and thereby the use) of shared micro-mobility would contribute to equity targets, would it also contribute to cost-efficiency and sustainability targets? At the moment, this seems questionable, at least, and research has only begun to establish the impact of shared micro-mobility on these topics. For example, shared e-scooters, mostly due to rebalancing, appear to have substantially higher life-cycle greenhouse gas emissions than shared bikes or public transportation (de Bortoli and Christoforou, 2020; Hollingsworth et al., 2019; Moreau et al., 2020).

Still, there might be 'low-hanging fruits', i.e. measures that require little or no public investment, yet have the potential to increase the accessibility, equity of access, sustainability and/or the efficiency of public transportation systems. Policy makers can, for example, require shared micro-mobility service providers to reposition their vehicles evenly by a measure of population density to increase equity of access at zero public costs. First evidence further suggests that shared micro-mobility can fill gaps in the existing transportation system where other modes are not available (Reck et al., 2021a). Thus, improving their availability when and where needed (e.g., at night in 'transit deserts') seems sensible. In general, by improving access at places where their use is wanted from a policy-perspective (i.e., public transportation stations to improve first/last mile access; at workplaces, to foster their use as alternative commuting modes; at accessibility voids) and prohibiting parking where their use is not wanted, policy makers can guide their use and integration into the wider transportation system. The two providers of shared (e-) bikes in Zurich have taken first steps in this direction and explore partnerships with large employers in the region to foster their use for commutes. While results for dockless e-bikes are not yet measurable, previous analyses suggest that docked (e-) bikes are indeed more often being used for commutes than other shared micro-mobility modes (Reck et al., 2021a). This analysis further shows that their users live in households with fewer private cars and less access to cars. While more work is needed to establish causation, this suggests that shared micro-mobility - if implemented and regulated sensibly - can contribute to more accessible, sustainable, and equitable cities.

We acknowledge that the number of respondents in our study varied by mode and that thus not all potentially relevant variables, in particular for the smallest subgroup of shared dockless e-bike users, were significant. Future studies could target larger samples of shared micro-mobility users to test our findings and extend them. Our results further call for mode choice studies that include shared micro-mobility to estimate the relevance of potentially new attributes (e.g., access, fun) and their impact on price.

CRediT AUTHORSHIP CONTRIBUTION STATEMENT

D.J. Reck: Conceptualization, Methodology, Data collection, Data analysis, Writing - original draft. K.W. Axhausen: Conceptualization, Methodology, Writing - review & editing.

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4. MODE CHOICE, SUBSTITUTION PATTERNS AND ENVIRONMENTAL IMPACTS OF SHARED AND PERSONAL MICRO-MOBILITY

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ABSTRACT

Shared micro-mobility services are rapidly expanding yet little is known about travel behaviour. Understanding mode choice, in particular, is quintessential for incorporating micro-mobility into transport simulations in order to enable effective transport planning. We contribute by collecting a large data set with matching GPS tracks, booking data and survey data for more than 500 travellers, and by estimating a first choice model between eight transport modes, including shared e-scooters, shared e-bikes, personal e-scooters and personal e-bikes. We find that trip distance, precipitation and access distance are fundamental to micro-mobility mode choice. Substitution patterns reveal that personal e-scooters and e-bikes emit less CO_2 than the transport modes they replace, while shared e-scooters and e-bikes emit more CO_2 than the transport modes they replace. Our results enable researchers and planners to test the effectiveness of policy interventions through transport simulations. Service providers can use our findings on access distances to optimize vehicle repositioning.

4.1 INTRODUCTION

The usage of shared micro-mobility services has greatly increased in recent years. This development is perhaps best documented in the USA, where 35M rides were recorded in 2017, 84M rides in 2018 and 136M rides in 2019 (NACTO, 2020). Many shared micro-mobility companies have since expanded around the globe and now offer their services in North American, European, Asian and Australian metropolises. In addition to the investor-led diffusion of shared micro-mobility services, the COVID-19 pandemic has expedited the diffusion of personal micro-mobility as alternatives to other means of commute.

Given their rapid diffusion, effective regulation and integrated transport planning of micro-mobility vehicles and services is pertinent. City administrations are further asking how micro-mobility can contribute to increasingly stringent CO_2 reduction targets. Advances in these directions, however, are hindered by our limited understanding of travel behaviour. Most importantly, we do not yet comprehensively understand mode choice between shared micro-mobility services and more established modes (e.g., public transport, private cars). Closing this gap is paramount: mode choice is one of the four essential 'ingredients' to conventional transport planning. Mode choice models that are based on revealed preference data further reveal *distance-based* substitution patterns[13] that enable more precise calculation of net environmental impacts than *trip-based* substitution patterns from survey-based methods. In the words of Ortúzar and Willumsen (2011: 207), "the issue of mode choice is probably the single most important element in transport planning and policy making".

The scope of the existing empirical literature on shared micro-mobility services strongly varies by mode. While travel behaviour with shared bikes is relatively well understood (e.g., Fishman et al., 2013; Ricci, 2015; Fishman, 2016; Teixeira et al., 2021), the literature on shared e-bikes is more limited (e.g., Campbell et al., 2016; Guidon et al., 2019; He et al., 2019). Shared e-scooters are the latest addition to the micro-mobility mix and researchers have only recently begun to analyse them (e.g., Christoforou et al., 2021; McKenzie, 2019; Noland, 2021; Wang et al., 2021, Younes et al., 2020). Most studies analyse patterns in user

[13] We find the following definition of modal substitution by Wang et al. (2021: 4) useful: "Modal substitution means that a certain number of trips made by a new mode of travel displace trips that would have been made by an existing mode; users substitute the new mode for an existing one (e.g. e-scooter substitutes for walking)."

characteristics or trip characteristics of a single mode, or compare data on different modes. While they provide valuable indications on factors influencing the choice of a single mode, they cannot explain their relative influence in choice situations between multiple competing modes. To the best of our knowledge, only one study has previously estimated a mode choice model between several shared micro-mobility services (Reck et al., 2021a). That study's use for integrated transport planning is limited, however, as it includes neither public transport and private modes, nor user characteristics.

We contribute by estimating the first mode choice model that includes shared micro-mobility services (e-scooters and e-bikes), public transport, private modes (bike, car, e-bike, e-scooter) and walking, as well as user characteristics. To do so, we conducted a large-scale empirical study with 540 participants in Zurich, Switzerland. For each participant, we collected three months of GPS traces through a smartphone app, booking data for rides conducted with shared micro-mobility services, and socio-demographic information through two surveys. Additionally, we collected GPS points of all available shared micro-mobility vehicles in Zurich at a five-minute interval for the same period through the providers' APIs (48M GPS points). We then matched all trips (65K) with selected contextual information (e.g., weather, available vehicles in close vicinity), user characteristics and non-chosen alternatives, and estimated mode choice using a mixed logit model. Finally, we demonstrate the practical utility of the model by deriving precise, distance-based substitution rates for shared micro-mobility services and their privately-owned counterparts, and by calculating their net environmental impacts.

This paper is structured as follows. In Section 2, we review the literature on shared micro-mobility mode choice. In Section 3, we introduce our data and the empirical context of our study. We develop the methodology, estimate the choice model and present the results in Section 4. In Section 5, we use the estimated model to derive substitution rates and to calculate the net environmental impacts of shared and personal e-bikes and e-scooters. We conclude with a discussion of the results and their implications for research, policy and practice in Section 6.

4.2 LITERATURE REVIEW

This section introduces the key results of previous studies on shared micro-mobility services. We focus on aspects that are hypothesized to influence mode choice, such as user and household characteristics as well as trip and context characteristics. This literature review both aims to synthesize general patterns that are found to hold across all shared micro-mobility services, as well as highlight differences between individual services to inform subsequent model specification.

Users of shared micro-mobility services are typically young, university-educated males often with full-time employment and few to no children and cars in their households (NACTO, 2020; Reck and Axhausen, 2021; Shaheen and Cohen, 2019; Wang et al., 2021). Users of shared e-bikes, in particular, also include a higher shares of middle age groups (He et al., 2019) while users of shared e-scooters appear to be particularly young (NACTO, 2020; Reck and Axhausen, 2021; Sanders et al., 2020; Wang et al., 2021). Income distributions, in particular for shared e-scooter users, vary by region, but generally correspond to the regional median income (NACTO, 2020; Reck and Axhausen, 2021). Vehicle ownership appears to correlate with shared vehicle usage, i.e. those who own e-scooters/e-bikes are more likely to use shared e-scooters/e-bikes as well (Fishman et al., 2013; Reck and Axhausen, 2021; Shaheen et al., 2011).

Trips with shared micro-mobility services are shorter than with other motorized modes of transport (e.g., private cars, public transport). Shared e-scooters, for example, are used for short distances and most frequently in central business districts or near universities (Bai and Jiao, 2020; Caspi et al., 2020; Hawa et al., 2021; Reck et al., 2021b; Zuniga-Garcia and Machemehl, 2020). Shared e-bikes are used for longer distances than e-scooters or regular bikes, often uphill (Du et al., 2019; Guidon et al., 2019; Guidon et al., 2020; He et al., 2019; Lazarus et al., 2020; MacArthur et al., 2014; Reck et al., 2021b; Shen et al., 2018; Younes et al., 2020). Precipitation and low temperatures negatively influence the usage of all shared micro-mobility services (El-Assi et al., 2017; Gebhart and Noland, 2014; Noland, 2019; Noland, 2021; Zhu et al., 2020). The evidence on use by time of day for shared e-scooters is inconclusive: some studies find evidence of two commuting peaks (Caspi et al., 2020; McKenzie, 2019), others only find single afternoon usage peaks (Bai and Jiao, 2020; Mathew et al., 2019; Reck et al., 2021b; Younes et al., 2020). In comparison to shared docked bikes, commuting use of shared e-scooters seems to be less pronounced (McKenzie, 2019; Reck et al., 2021a; Younes et al., 2020). Finally, vehicle access distance appears to influence usage (Christoforou et al., 2021).

The above studies provide valuable indications on factors influencing the choice of a single shared micro-mobility mode. However, they cannot explain the relative influence of factors in choice situations between multiple competing modes. To the best of our knowledge, only one study has previously estimated mode choice models between several shared micro-mobility services based on revealed preference data. Reck et al. (2021a) collected trip-level data of four different shared micro-mobility modes in Switzerland and estimated a matching mode choice model. Findings include that shared micro-mobility mode choice is dominated by distance, elevation rise, and time of day. While docked (e-)bikes are preferred for longer distances and during commuting times, dockless e-scooters are preferred for shorter distances and during the night. The density of available vehicles at the point of departure further influences mode choice (this effect is strongest for dockless fleets). Two key limitations of this study are that it does not include other transport modes (e.g., public transport, private cars) nor user characteristics.

We contribute by collecting a first comprehensive data set that includes revealed preference data on trips conducted with different shared micro-mobility services (e-scooters, e-bikes), public transport, private modes (bike, car, e-bike, e-scooter) and walking, and by estimating a mode choice model between all eight transport modes.

4.3 DATA

4.3.1 Location and recruitment

Our study is conducted in Zurich, which is Switzerland's largest city with 403K inhabitants in the city and 1.5M inhabitants in the metropolitan area. Zurich has a high trip-level public transport mode share of 41% according to the latest Swiss mobility census (MZMV, 2015). The share of trips conducted with private cars has been declining steadily over the past years from 40% in 2000 to 25% in 2015. The remaining trips are conducted with active modes (walking: 26%, (e-) bikes: 8%). Several micro-mobility companies operate in Zurich making it a suitable place to study their usage. They include docked (e-)bikes (Publibike), dockless e-bikes (Bond) and dockless e-scooters (e.g., Lime, Bird, Tier, Voi).

Data collection began in June 2020. The cantonal statistical office sent invitations to participate in our mobility study to 10 000 randomly selected inhabits of Zurich municipality of age 18 to 65 by post. Each invitation included a QR code and a link, each directing interested participants to the online survey. The study included two surveys and three months of GPS smartphone tracking. Respondents were offered an incentive of 90 CHF[14] for their participation. All invitation letters included detailed information on the purpose of the study and the methods to collect and process the data in compliance with the EU General Data Protection Regulation. The study design was reviewed and approved by the university's Ethics Committee without reservations.

A total of 1 277 people returned the first survey between June and July 2020. No follow-up activities were undertaken to maximize the sample size. The resulting response rate of 12.7% is well in the expected range for a survey with a considerable response burden (i.e., the effort required to answer a questionnaire) of 643 points (calculated using the method proposed by Schmid and Axhausen, 2019). Only respondents who completed the first questionnaire were invited to participate in the subsequent GPS tracking and the final survey. A total of 540 (6%) respondents completed the entire study and their data is used for the analyses in this paper. The subsequent subsections introduce each data source (survey, GPS tracks, booking records, contextual data) and discuss the representativeness of our sample.

4.3.2 Data sources

We designed two online surveys of which only the first is used in this study. The survey (see Appendix A.2 for the German version and Appendix A.3 for the English version) included questions about socio-demographic and mobility-related information. All questions and answer categories were formulated to be equal to the latest available Swiss mobility census to enable direct comparison. Documentation in English[15] and questionnaires in German[16] and French[17] are available online. The survey is structured in the following three main blocks:

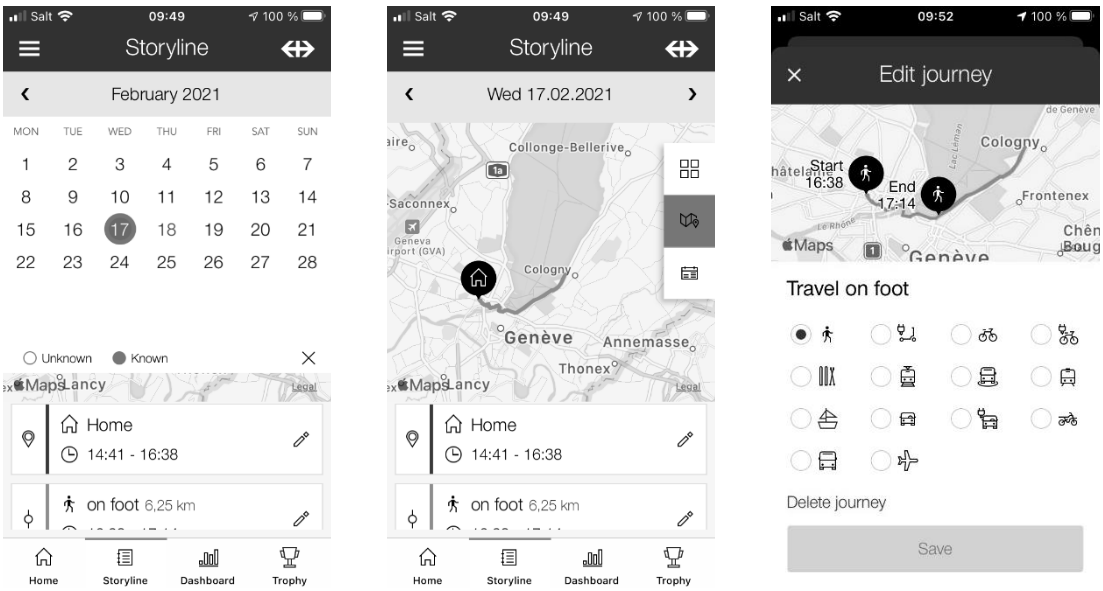
- person-specific socio-demographic questions (e.g., year of birth, gender, educational attainment, current occupation),

[14] 1 CHF = 1.08 USD at the time of writing (29 June 2021).
[15] https://www.are.admin.ch/are/en/home/mobility/data/mtmc.html
[16] https://www.bfs.admin.ch/bfs/de/home/statistiken/mobilitaet-verkehr/erhebungen/mzmv.assetdetail.5606052.html
[17] https://www.bfs.admin.ch/bfs/fr/home/statistiques/mobilite-transports/enquetes/mzmv.assetdetail.5606053.html

- household-specific socio-demographic questions (e.g., number of adults and children, monthly income, vehicle ownership), and
- person-specific mobility questions (e.g., public season ticket ownership, travel priorities, knowledge of and accounts in shared (micro-) mobility schemes, frequency of use, access to shared micro-mobility services at home and work).

The smartphone app 'MyWay' (available in app stores) was used for GPS tracking. The app passively collects GPS traces, identifies trips and infers the transport mode used based on a comparison with public transport timetables and past user mode choice. Each day, the app presents users with a summary of their realized trips and allows retrospective editing of transport modes. Figure 7 gives a visual impression of the user interface. Overall, we collected 65 716 trips for 540 respondents with this method, which further divide into 17 004 public transport trips, 16 211 car trips, 15 393 walking trips, 14 246 bike trips, 2 537 e-bike trips, and 345 e-scooter trips.

Figure 7 GPS tracking app on iPhone SE (left: calendar view, middle: map view, right: edit mode view).



We further received booking data for all shared micro-mobility trips booked by our participants during the study duration through a new intermodal journey planning app 'yumuv' (available in app stores), which was launched by Swiss Federal Railways in June 2020. Matching these booking records with the GPS tracks allowed us to differentiate private from shared micro-mobility trips. Out of the total of 2 537 e-bike trips, 287 had matching booking records and were hence labelled as shared e-bike trips. Out of the total of 345 e-scooter trips, 121 had matching booking records.

Finally, we added contextual data to each trip. This includes weather data (openly available[18] in ten-minute intervals for Zurich), as well as the distance to the next available shared micro-mobility vehicle at the beginning of each trip. In order to compute the latter, Swiss Federal Railways records the locations of all shared micro-mobility vehicles in Zurich in five-minute intervals through the providers' APIs.

4.3.3 Representativeness

We compare the characteristics of our sample to the latest censuses to investigate its representativeness. The latest available censuses are the 2018 "Strukturdatenerhebung" (SE) and the 2015 mobility census "Mikrozensus Mobilität und Verkehr" (MZMV). While the former is more current, the latter includes substantially more information on mobility-related topics.

Table 11 shows the resulting comparison. Our sample is slightly younger (mean: 38 years) than the respondents of both previous censuses (2015: 42 years, 2018: 41 years). It further includes slightly fewer females (46%) than previous censuses (2015: 50%, 2018: 51%). The three successive surveys (2015, 2018, 2020) further show two larger societal trends: an increasing share of respondents holding a tertiary degree (2015: 49%, 2018: 58%, 2020: 76%) and an increasing share of respondents in full-time employment (2015: 63%, 2018: 68%, 2020: 81%). In line, the mean monthly household income increased from 2015 (~9 000 CHF) to 2020 (~10 000 CHF). The household structure further exhibits a trend towards single/dual adult households (2015: 71%, 2018: 84%, 2020: 85%) without children (2015: 62%, 2018: 70%, 2020: 73%). Households in our sample owned slightly fewer cars and slightly more bikes and e-bikes compared to the 2015 census. They further owned slightly more nationwide and therefore slightly fewer local public transport season tickets.

[18] https://data.stadt-zuerich.ch/dataset/sid_wapo_wetterstationen

Table 11 Comparison of survey respondents and recent censuses. All values in %.

	This survey	Census (SE)	Census (MZMV)
Year	2020	2018	2015
N (Zurich municipality only)	540	7 808	809
Filtered for age groups	18-65	18-65	18-65
Person-specific attributes			
Age			
18-20	0	3	2
21-30	26	20	16
31-40	38	31	28
41-50	23	22	25
51-60	8	18	21
61-65	5	7	8
Female	46	50	51
Education (tertiary degree)	76	58	49
Full-time employed	81	68	63
PT season ticket ownership			
Nation-wide	19	n/a	16
Local (Zurich)	38	n/a	43
Household-specific attributes			
Monthly income			
4 000 CHF and below	17	n/a	11
4 001 CHF - 8 000 CHF	21	n/a	35
8 001 CHF - 12 000 CHF	23	n/a	26
12 001 CHF - 16 000 CHF	25	n/a	14
16 000 CHF and above	13	n/a	14
Children			
0	73	70	62
1	12	14	17
2 and above	15	15	20
Adults			
1	26	28	15
2	62	56	56
3 and above	12	15	29
Cars			
0	46	n/a	45
1	45	n/a	43
2 and above	9	n/a	11
Bikes			
0	16	n/a	19
1	20	n/a	25
2 and above	63	n/a	56
E-bikes			
0	86	n/a	95
1	10	n/a	4
2 and above	4	n/a	1
E-Scooters			
0	97	n/a	n/a
1	3	n/a	n/a
2 and above	0	n/a	n/a

4.4 MODE CHOICE

In this section, we estimate the mode choice model and present the results.

4.4.1 Method

We first generate the choice sets by complementing each of the 65 716 observed trips in our GPS tracking data with the data for the non-chosen alternatives. For each observed trip, we calculate the non-chosen alternatives with the agent-based transport simulation software MATSim (Horni et al., 2016). The MATSim Zurich scenario has been used extensively in transport planning research (e.g., Balac et al., 2019; Becker et al., 2020; Hörl et al., 2021; Manser et al., 2020) and provides reliable attribute values for the non-chosen alternatives. Due to reasons described earlier, MATSim is limited to public transport, private cars, private bikes and walking. While we can safely assume that e-bikes and e-scooters are used on the same routes as private bikes (thus, distances of these alternatives are equal), travel times are likely to differ. Thus, we constrain our models to use distance parameters only and exclude travel time parameters.

In addition to trip-specific attributes (distance, access distance, transfers, elevation, time of day), we include weather (precipitation, wind) and a number of binary person-specific attributes that have previously been hypothesized to influence micro-mobility mode choice. These include public transport season ticket ownership (local, nation, bundle[19]), the number of vehicles in the household (cars, bikes, e-bikes, e-scooters), age, gender, university education and employment status. Prices were not included in this choice model as they are heavily correlated with distances for many transport modes such as private cars, shared e-scooters and shared e-bikes, and their inclusion would thus lead to multicollinearity issues. For example, the shared e-bike operator in Zurich charges an unlocking fee of 1 CHF and an additional per-kilometre fee of 1 CHF. Table 12 summarizes all attributes used for subsequent model estimation.

[19] Transport bundles sold in Zurich during the time of study included a local public transport season ticket and a 60-minute monthly allowance for shared micro-mobility services.

Table 12 Attributes used for model estimation (trip-level statistics).

Attribute	Unit	Min.	1st Qu.	Med.	Mean	3rd Qu.	Max.
Trip-specific attributes							
Distance	km	0.01	1.35	3.01	4.15	5.60	80.28
Access distance[1]							
PT	km	0.01	0.29	0.42	0.45	0.56	4.30
Shared e-bike[2]	km	0.00	0.13	0.22	0.23	0.33	0.50
Shared e-scooter[2]	km	0.00	0.04	0.07	0.09	0.12	0.50
Transfers	count	0.00	0.00	1.00	1.00	1.00	4.00
Elevation	km	-0.47	-0.02	0.00	0.00	0.02	0.47
Morning (6 a.m. - 9 a.m.)	binary	0%	0%	0%	0%	0%	100%
Night (9 p.m. - 5 a.m.)	binary	0%	0%	0%	0%	0%	100%
Weather							
Precipitation	mm/h	0.00	0.00	0.00	0.16	0.05	6.14
Wind speed	m/s	1.22	3.56	4.73	5.26	6.19	18.68
Person-specific attributes							
PT season ticket (local)	binary	0%	0%	0%	40%	100%	100%
PT season ticket (nation)	binary	0%	0%	0%	18%	0%	100%
PT season ticket (bundle)	binary	0%	0%	0%	4%	0%	100%
Cars in household	count	0.00	0.00	1.00	0.64	1.00	5.00
Bikes in household	count	0.00	1.00	2.00	2.25	3.00	6.00
E-bikes in household	count	0.00	0.00	0.00	0.18	0.00	3.00
E-scooters in household	count	0.00	0.00	0.00	0.03	0.00	2.00
Age	years	19	30	36	38	45	65
Female	binary	0%	0%	0%	46%	100%	100%
University education	binary	0%	0%	100%	74%	100%	100%
Full-time employment	binary	0%	0%	100%	69%	100%	100%

[1] access distance is only defined for public transport and shared micro-mobility services.
[2] when available.

In order to account for taste heterogeneity in mode choice between individuals, we choose a mixed logit model in panel specification[20] and include random alternative-specific constants (Hensher and Greene, 2003; McFadden and Train, 2000). We built and estimated the model iteratively (i.e., dropping insignificant and insubstantial variables) to obtain the most parsimonious model possible that simultaneously allows for cross-modal comparisons. Note that the final model includes four non-linear variables: a squared term for trip distance and interaction terms between trip distance and precipitation, elevation and wind speed. For model estimation, we used maximum likelihood

[20] The repeated choice nature of panel data is recognized by Apollo and probabilities across individual choice observations for each individual are multiplied (Hess and Palma, 2019).

with 500 MLHS[21] draws in the R package Apollo (Hess and Palma, 2019). Appendix A.1 shows the utility functions.

Finally, we set the availabilities. For each person, we verify if each transport mode was used at least once during the three months. If not, we set the availability of the respective transport mode to zero for all trips of that person, i.e. remove it from the choice set for this person. Further, we set the availability of shared e-scooters, shared e-bikes and public transport to zero for each trip where no vehicle was detected within a 500m radius or no public transport connection was found.

4.4.2 Results

Table 13 displays the estimation results. The mixed logit model has an excellent fit with an adjusted rho-square value of 0.44. In comparison to the reference mode (walking), trip distance substantially and significantly influences mode choice for all other modes. Precipitation positively influences mode choice for public transport and cars, and negatively for all micro-mobility modes, most so for shared e-bikes and e-scooters. Elevation and wind speed further negatively influence mode choice for non-electric bikes.

One perhaps surprising result concerns the penalty of the access distance for public transport and shared e-bikes and e-scooters. Access distance for shared e-scooters is penalized substantially more (-6.16) than access distance for public transport and shared e-bikes (-2.31 and -2.36, respectively)[22]. Users of shared e-scooters are willing to walk an average of 60m and a maximum of 210m to access a vehicle, while users of shared e-bikes are willing to walk an average of 200m and up to 490m to access a vehicle. Public transport users are willing to walk even longer (average: 400m) to reach their preferred stop. We offer two explanations for this behaviour. First, shared e-scooters are used for substantially shorter distances than both other modes. Hence, a 200m access distance relative to the overall trip distance is substantially more for shared e-scooters and thus presents a greater relative burden. Second, shared e-scooters cannot be pre-reserved in Zurich. The longer the access distance, the more uncertainty in availability users face. For public transport real-time information about vehicle locations is available through major trip planning apps (e.g.,

[21] MLHS draws avoid undesirable correlation patterns that arise when standard Halton sequences are used for several variables (Hess et al., 2006).

[22] Additional saturation effects of the density of shared micro-mobility fleets were not found.

Google Maps or the city's public transport app) and Zurich's shared e-bikes can be pre-reserved for up to ten minutes.

Several further parameter estimates show the expected results and are thus only briefly mentioned here. For public transport, season tickets positively influence mode choice while transfers negatively influence mode choice. The transport bundle further positively influences mode choice for shared e-scooters. Vehicles ownership positively influences mode choice for each respective mode. Time of day is significant at a 95% confidence level only for personal e-bikes and shared e-scooters, positively influencing mode choice during the morning commute (6 a.m. - 9 a.m.) for personal e-bikes and mode choice during the night (9 p.m. - 5 a.m.) for shared e-scooters. Most socio-demographic parameter estimates are insignificant at a 95% confidence level, except for full-time employment, which positively influences mode choice for shared e-bikes.

Table 13 Estimation results (mixed logit model).

	PT		Car		Bike		E-Bike (personal)		E-Bike (shared)		E-Scooter (personal)		E-Scooter (shared)	
	Coef.	t.rat.	Coef.	t.rat.	Coef.	t.rat.	Coef.	t.rat.	Coef.	t.rat.	Coef.	t.rat.	Coef.	t.rat.
ASC (μ)	-3.97	-58.57	-5.40	-43.34	-3.47	-44.60	-4.73	-25.39	-5.52	-7.97	-4.85	-13.34	-4.35	-7.88
ASC (σ)	-1.16	-45.41	-1.56	-42.84	-1.64	-41.59	-1.47	-17.00	-1.53	-8.29	1.51	11.16	0.36	2.08
Distance	2.09	106.27	1.94	72.79	1.63	67.15	1.74	43.67	2.26	17.51	1.62	9.68	1.32	11.38
Distance * Distance	-0.04	-46.93	-0.03	-40.96	-0.03	-24.70	-0.03	-13.59	-0.09	-5.84	-0.07	-2.85	-0.02	-1.65
Distance * Precipitation	0.75	4.21	0.74	4.09	-0.74	-3.96	-0.79	-2.86	-4.13	-3.00	-0.58	-0.84	-4.27	-1.64
Distance * Elevation					-0.15	-3.59								
Distance * Wind speed					-0.61	-4.73								
Access distance	-2.31	-35.46							-2.36	-1.95			-6.16	-2.89
PT transfer	-0.64	-29.23												
Morning (6 a.m. - 9 a.m.)							0.34	4.43	-0.18	-0.72	0.59	2.26	0.23	0.83
Night (9 p.m. - 5 a.m.)							-0.15	-1.32	-0.31	-1.09	0.91	3.57	0.35	1.23
Vehicles in household			1.13	23.62	0.18	8.37	1.53	20.83			4.99	11.75		
PT season ticket (local)	0.93	14.13												
PT season ticket (nation)	0.91	7.65												
PT season ticket (bundle)	0.31	4.45							-0.32	-1.12			1.80	7.92
Age									0.02	0.55			-0.01	-0.65
Female									0.55	0.65			-0.74	-1.70
University education									0.05	0.05			-0.18	-0.50
Full-time employment									1.49	2.61			0.51	1.53
Number of individuals	540													
Number of observations	65 716													
Adj. Rho-square	0.44													

4.5 SUBSTITUTION PATTERNS AND ENVIRONMENTAL IMPLICATIONS

In this section, we first utilize the estimated choice model to derive substitution patterns[23] for each micro-mobility mode. Using these substitution patterns, we then calculate net CO_2 emissions.

4.5.1 Substitution patterns

Methodologically, only a slight adaption to the above choice model is necessary to derive substitution patterns. We take the subsets of trips conducted with e-scooters and e-bikes and set the availability for each mode, when chosen, from one to zero. We then apply our model to the subset of trips with adjusted availabilities to predict alternative mode choice. Conceptually, this predicted alternative mode is equal to what is commonly described as a substituted mode, i.e. the mode that would have been chosen if the chosen mode had not been available. Using the new predictions, we can calculate average substitution rates for e-scooters and e-bikes on a trip-level and on a km-level. For the trip-level, we divide the number of trips with a particular substituted mode (e.g., public transport) by the total number of trips conducted with the micro-mobility mode (e.g., shared e-scooters). For the km-level, we divide the total distance with a particular substituted mode by the total distance with the micro-mobility mode.

The resulting substitution patterns are shown in Table 14. We observe that personal e-bikes replace trips conducted with all four main modes (walk, PT, car, bike), while shared e-bikes replace substantially fewer car trips and more PT and bike trips. While personal e-scooters show a similar substitution pattern to personal e-bikes with the exception of replacing more walk and fewer car

[23] Substitution patterns (or 'substitution rates') can also be elicited with surveys, i.e. by asking participants about their last trip and their alternative mode choice. Indeed, this approach is much more common than the choice model approach developed here. The latter, however, has one key advantage over the former: it allows to calculate precise, distance-based substitution patterns. These are more adequate for estimating environmental implications than trip-based substitution patterns stemming from surveys for three reasons. First, it is substituted distance and not substituted trips that matters when calculating environmental implications. Second, substitution patterns derived from choice models are valid for all trips, not just the ones explicitly asked for, as they build on user preferences. Third, substitution patterns derived from choice models are more reliable than those derived from stated preference surveys, which are prone to biases such as the recall bias or the social desirability bias. Hence, we chose to proceed with the choice model approach instead of detailing the results from survey data, which we also elicited.

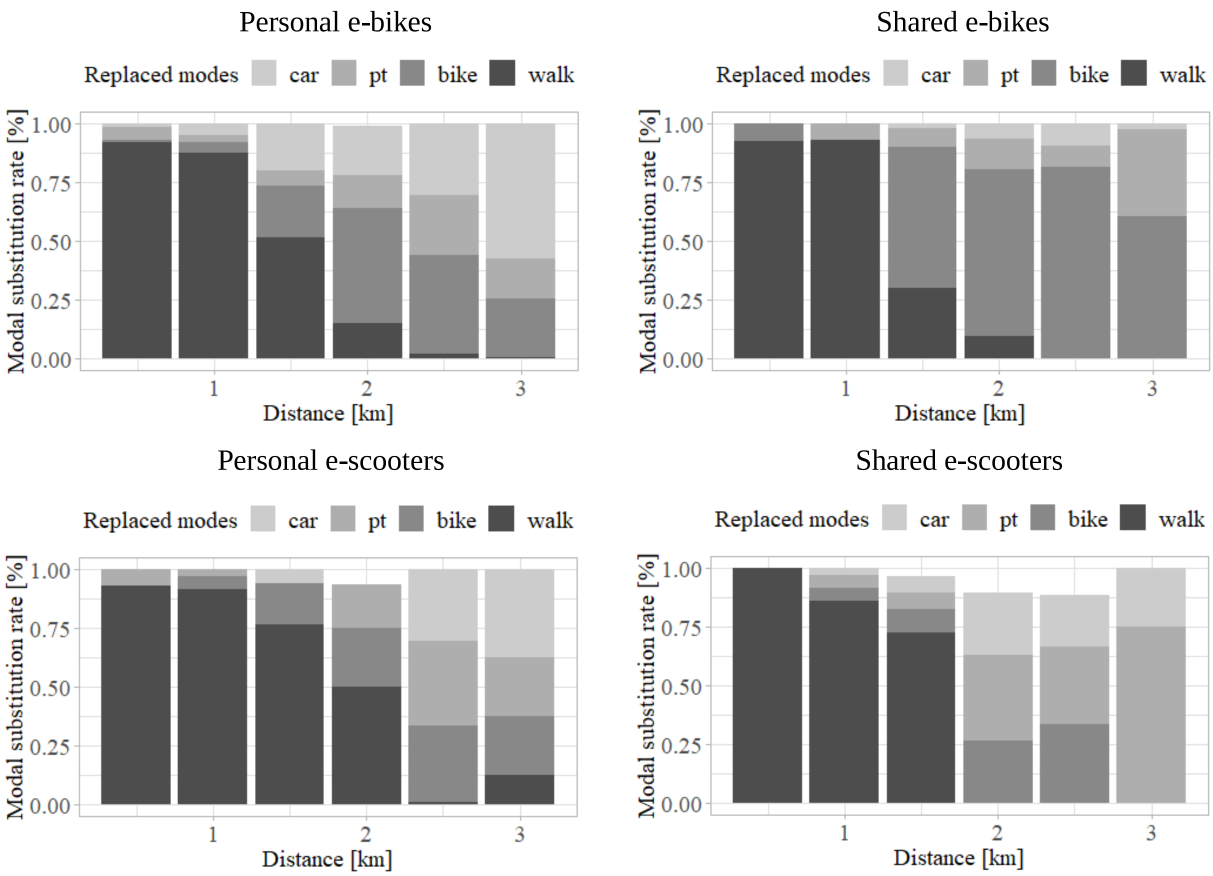
trips, shared e-scooters predominantly replace walk and PT trips. In general, the trip-level substitution rates exhibit a higher share of walking trips than the km-level substitution rates. The reason is that walking trips are comparatively short, thus have less impact in distance-based measures.

Table 14 Micro-mobility substitution rates (trip-level and km-level) derived from the mode choice model.

	E-Bike (personal)		E-Bike (shared)		E-Scooter (personal		E-Scooter (shared)	
Mode	trip	km	trip	km	trip	km	trip	km
Walk	27%	9%	26%	10%	36%	19%	52%	26%
PT	21%	30%	32%	50%	23%	28%	23%	47%
Car	32%	43%	6%	8%	22%	31%	10%	12%
Bike	20%	17%	36%	32%	20%	22%	12%	12%
E-Bike (personal)			0%	0%	0%	0%	0%	0%
E-Bike (shared)	0%	0%			0%	0%	3%	3%
E-Scooter (personal)	0%	0%	0%	0%			0%	0%
E-Scooter (shared)	0%	0%	0%	0%	0%	0%		

One of the many advantages of this choice model-based approach to deriving substitution patterns is that precise distance measures for each trip are observed. For surveys, these are usually imprecise or simply not available as they are based on participants' memories of recent trips. Figure 8 displays substitution rates by distance brackets. Two general patterns emerge. For short trips, all micro-mobility modes mostly replace walking. As the distance grows, the shares of replaced public transport, bike and car trips increase. Personal e-bikes, however, replace personal cars substantially more often for longer distances than all other modes.

Figure 8 Substitution rates for micro-mobility modes by distance.



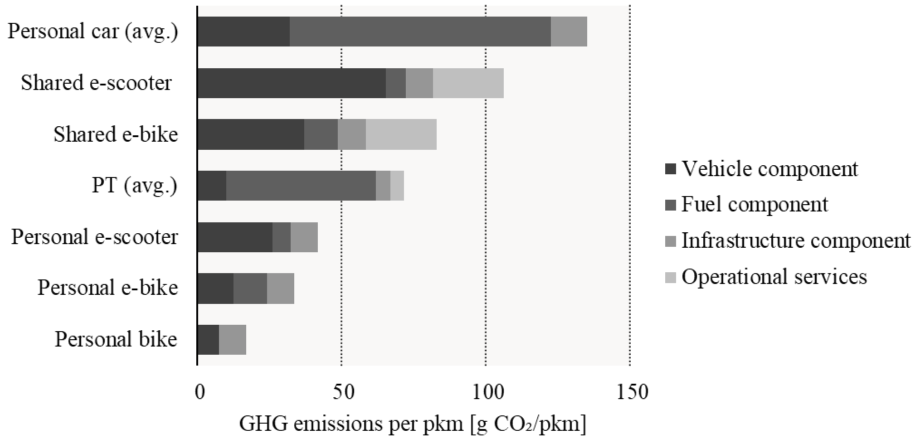
4.5.2 Environmental implications

The impact of a new transport mode on the sustainability of the surrounding transport system depends not only on the replaced modes, but also on their respective emissions. In this subsection, we integrate our findings on substitution patterns with previous findings on gross CO_2 emissions to calculate the net CO_2 emissions of the different micro-mobility modes.

Building on previous work from de Bortoli and Christoforou (2020) and Hollingsworth et al. (2019), the International Transport Forum (ITF, 2020a) recently conducted a comprehensive analysis of the life cycle emissions of emerging and more established transport modes. It took into account not only established components of such analyses (e.g., infrastructure wear, vehicle manufacturing, and fuel), but also developed a new component (operational services, e.g. rebalancing) which is a key differentiating characteristic and an emission driver of emerging modes such as shared micro-mobility services.

Figure 9 shows the emissions in g CO_2 per passenger kilometre (pkm) for all modes relevant to this study.

Figure 9 Life cycle CO_2 emissions per passenger kilometre of selected transport modes (adapted from ITF, 2020a).



We integrate these findings on CO_2 emissions with our findings on substitution patterns for shared and personal e-bikes and e-scooters to calculate their 'net emissions':

$$net\ emissions\ (mode) = gross\ emissions\ (mode) - \sum_i gross\ emissions\ (replaced\ mode_i) \qquad (1)$$

Consider the following (hypothetical) example: a shared e-scooter (106g CO_2 / pkm) replaces public transport (72g CO_2 / pkm) and walking (0g CO_2 / pkm) in equal amounts (i.e., 50% and 50%). The 'gross emissions' of shared e-scooters are 106g CO_2 / pkm. The gross emissions of the replaced modes are 36g CO_2 / pkm (calculate: 50% * 72g CO_2 / pkm + 50% * 0g CO_2 / pkm). The resulting net emissions of shared e-scooters are thus 70g CO_2 / pkm. Positive net emissions can be interpreted as the additional emissions caused per pkm by the new mode. In turn, negative net emissions can be interpreted as the emissions saved per pkm by the new mode.

Table 15 shows the resulting net emissions using the previously derived km-level substitution rates for all four micro-mobility modes. Note that only km-level substitution rates (i.e., not trip-level substitution rates) can be used for this type of analysis as trip-level substitution rates are biased towards short walk trips (see comparison in Table 14). We find that the CO_2 emissions of personal e-bikes (34g CO_2 / pkm) and personal e-scooters (42g CO_2 / pkm) are lower than the average CO_2 emissions of the modes they replace (83g CO_2 / pkm and 66g CO_2 / pkm, respectively). Shared e-bikes and shared e-scooters exhibit the opposite pattern: their CO_2 emissions are higher than the average CO_2 emissions of the modes they replace. Hence, from a short-term mode choice perspective and under current conditions, only personal e-bikes and e-scooters contribute to making transport more sustainable. All values can be regarded as lower limits as a certain share of trips can be assumed to be induced (i.e., not replacing previous trips), further adding to CO_2 emissions.

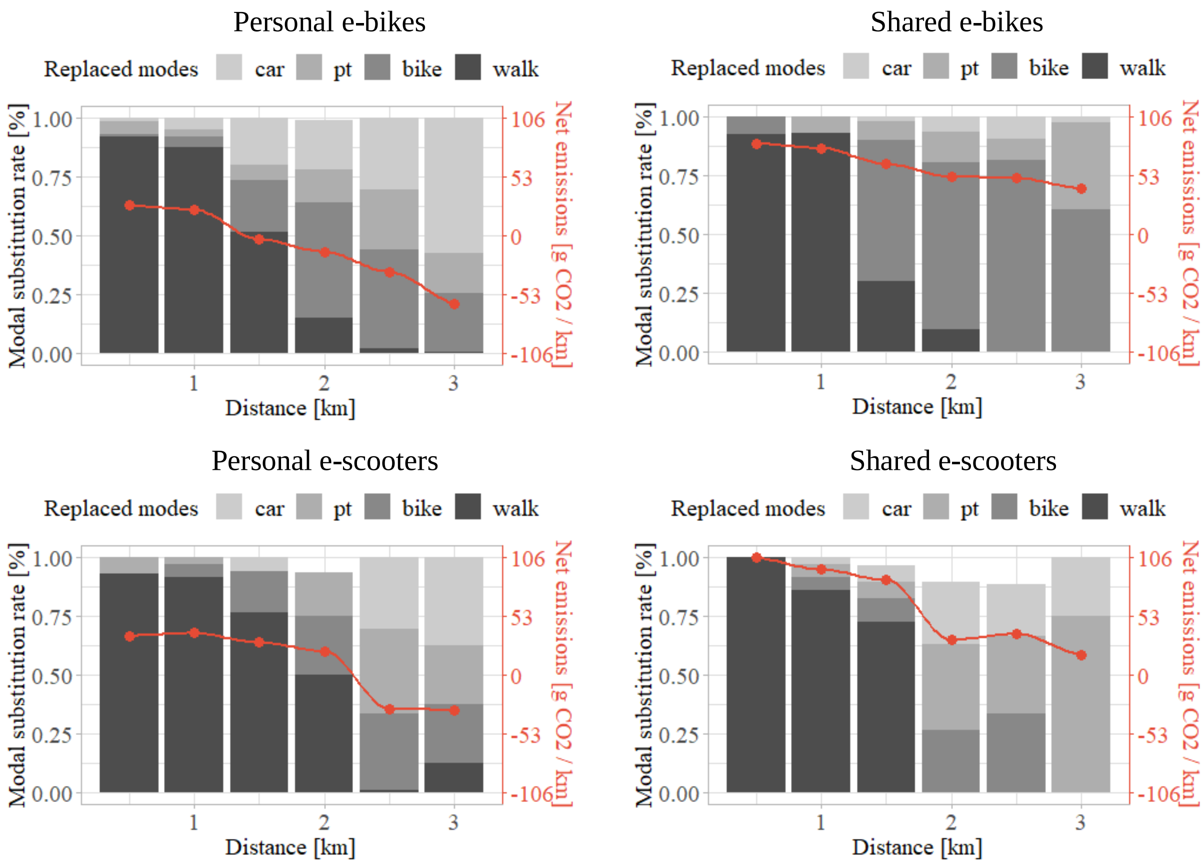
Table 15 Average micro-mobility net emissions after substitution effects.

Substituted mode	Gross emissions [g CO_2 / pkm]	Substitution patterns (km-level) by micro-mobility mode			
		E-Bike (personal)	E-Bike (shared)	E-Scooter (personal)	E-Scooter (shared)
Walk	0†	9%	10%	19%	26%
PT (avg.)	72†	30%	50%	28%	47%
Car (avg.)	135†	43%	8%	31%	12%
Bike	17†	17%	32%	22%	12%
E-Bike (personal)	34†		0%	0%	0%
E-Bike (shared)	83†	0%		0%	3%
E-Scooter (personal)	42†	0%	0%		0%
E-Scooter (shared)	106†	0%	0%	0%	
Emissions of substituted modes		83	52	66	55
Emissions of micro-mobility mode		34†	83†	42†	106†
Net emissions [g CO_2 / pkm]		**-49**	**31**	**-24**	**51**

† Emission calculations drawn from ITF (2020a).

Finally, we know that substitution patterns vary with trip distance (cf. Figure 8). Hence, net emissions will differ by distance bracket. Figure 10 visualizes this relationship. We find that net emissions for personal e-bikes and e-scooters are positive for short distances as they predominantly replace walking for short trips. For longer distances, they replace cars and public transport substantially more often, resulting in overall negative net emissions. Net emissions of shared e-bikes and e-scooters are positive regardless of the distance bracket.

Figure 10 Replaced modes (stacked bars) and resulting per-kilometre net emissions (dots/line) for micro-mobility modes by distance.



4.6 CONTRIBUTIONS AND CONCLUSIONS

This is the first study to collect revealed preference data for and to estimate a comprehensive mode choice model between several shared and personal micro-mobility modes (e-bikes, e-scooters) and more established transport modes (public transport, car, bike, walk). Our contributions to research, policy and practice are threefold.

First, our results build the foundation to incorporate micro-mobility into transport network simulations to understand and to forecast their impact at system level and under varying policy scenarios. All else equal, the choice model reveals that trip distance, precipitation and access distance are fundamental to shared micro-mobility mode choice. Users are willing to walk between ~60m and ~200m to access shared e-scooters and shared e-bikes, respectively. Pre-booking functionality decreases the disutility of larger access distances. These results are not only useful to researchers and practitioners aiming to extend transport network simulations, but can also inform service provider's decisions on how to optimize their vehicle repositioning schemes.

Second, we demonstrate how choice models can be used to derive distance-based substitution patterns. Distance-based substitution patterns are more adequate for estimating environmental implications than common trip-based substitution patterns that are elicited through surveys for several reasons. First, it is substituted distance and not substituted trips that matters when calculating environmental implications. Second, substitution patterns derived from choice models are valid for all trips, not just the ones explicitly asked for, as they build on user preferences. Third, substitution patterns derived from choice models are more reliable than those derived from stated preference surveys, which are prone to biases such as the recall bias or the social desirability bias. This methodological contribution will gain in relevance as further new mobility services are introduced and their environmental implications will need to be assessed.

Third, our results yield direct policy implications for cities aiming to reduce transport-related CO_2 emissions. We show that personal e-bikes and e-scooters emit less CO_2 than the transport modes they replace, while shared e-bikes and e-scooters emit more CO_2 than the transport modes they replace. This finding challenges a common vision in transport that 'sharing is caring' for the environment. For micro-mobility, the relationship indeed appears to be reverse. On the one hand, city administrations can use these insights to justify public subsidies for personal e-bike / e-scooter sales and investments in bike lanes to increase their mode share further. On the other hand, our results suggest caution when admitting and licensing shared micro-mobility providers. City administrations can collaborate with and require providers to improve the two main sources of CO_2 emissions of shared micro-mobility (operational services and vehicle manufacturing) while safeguarding their potential to improve transit catchment areas and to ease peak-time transit occupancy (e.g., Bielinski et al., 2021; de Bortoli and Christoforou, 2020; ITF, 2020a). While shared e-bikes and e-scooters might increase CO_2 emissions in the short-term, they could help spark sustainable mobility transitions in the long-term if usage leads to ownership. Clearly, longitudinal studies are needed to establish this relationship.

Finally, we acknowledge that this study has limitations. First, this study uses the gross CO_2 emissions for all transport modes as calculated in the ITF (2020a) life cycle assessment. While this is the most comprehensive life cycle assessment to date in terms of transport modes and included factors, the limitation is that it was conducted in Paris and not in Zurich. Gross CO_2 emission hence are likely to differ for some transport modes while they can be assumed to be similar for other transport modes such as shared e-scooters as the same companies operate in Paris and in Zurich. Second, the number of observations for shared e-scooter and shared e-bike trips is low (121 and 287, respectively) in comparison to other transport modes. This is testimony of their overall low market share but simultaneously limits the complexity of the estimated models. Finally, although COVID-19 incidence rates were comparatively low in Switzerland during the time of study[24], travel behaviour was still affected. Most of all, public transport usage remained lower than usual (Molloy et al., 2021b). Our study thus potentially over-estimates public transport substitution by other modes.

CRediT AUTHORSHIP CONTRIBUTION STATEMENT

Daniel J. Reck: Conceptualization, Methodology, Formal analysis, Investigation, Writing - original draft, Writing - review & editing. Henry Martin: Data pre-processing. Kay W. Axhausen: Conceptualization, Writing - review & editing.

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[24] The 7-day incidence rate per 100 000 inhabitants ranged between 1.4 on 1 June and 27.0 on 1 October. In comparison, the highest rate was reported on 11 November (666.3).

5. CONCLUSION AND OUTLOOK

The aim of this final chapter is to summarize the main contributions of this thesis, to reflect on their relevance for society, and to outline directions for future work.

5.1 MAIN CONTRIBUTIONS

In Chapter 1, I outlined a number of research questions that this thesis aims to address. Here, I return to these research questions, summarize the key results of this thesis, and explain how the contributions go beyond previous research. I finish with a discussion of the extent to which each research question has been answered and which aspects are outstanding.

5.1.1 Research questions

The following research questions (excerpt from a 2020 Call for Papers from the journal *Transportation Research Part D: Transport and Environment*) were posed at the outset of this thesis:

- "Use of shared micro-mobility: How does the use of different shared micro-mobility modes (e.g., bikes vs. e-bikes vs. e-scooters) differ across space and time? How can big data and new methods be used to advance our understanding of shared micro-mobility behavior?"
- "Correlates of shared micro-mobility: Who uses shared micro-mobility services? Do shared micro-mobility services benefit certain social groups more than others? Are there any equity concerns?"
- "Interactions with other modes: How do shared micro-mobility services affect the use of other transport modes? What is their potential for mode substitution in the long term? What are their traffic and environmental impacts?"

5.1.2 Summary of the key results

This thesis contributes to answering the research questions posed above by offering some of the first empirical evidence on users, mode choice, substitution patterns and net CO_2 emissions of shared micro-mobility services using the city of Zurich as a case study. The key findings elucidated across the three papers that form the core of this thesis are three-fold. First, users of all shared micro-mobility services tend to be young, university-educated males with full-time employment living in affluent households without children or cars. This pattern is particularly pronounced for shared dockless e-bikes and raises equity concerns regarding public investments in new infrastructure or redistributions of public space as relate to shared micro-mobility services. Second, mode choice for shared micro-mobility services is strongly influenced by trip distance, precipitation and access distance. Users in Zurich are willing to walk between ~60m and ~200m to access shared e-scooters and shared e-bikes, respectively. Docked (e-) bikes are further preferred during rush hours, while dockless e-scooters, in particular, are preferred during the night and at midday. Third, we derive distance-based substitution patterns for shared and personal e-scooters and e-bikes and calculate their net CO_2 emissions. Shared e-scooters and e-bikes mostly replace walking, cycling and public transport in Zurich. Hence, they emit more CO_2 than the transport mode mix they replace. Personal e-scooters and e-bikes, in contrast, replace car-based modes substantially more often. Hence, they emit less CO_2 than the transport mode mix they replace and contribute to making urban transport more sustainable.

5.1.3 Novelty of the results and contributions to the literature

The work presented in this thesis goes beyond previous research in several ways and makes two main contributions to research and practice. First, this thesis presents comprehensive empirical evidence on users and usage of several different shared micro-mobility services in a single city. This is novel as most previous studies analysed a single shared micro-mobility service[25] or compared two shared micro-mobility services[25] at most (e.g., Lazarus et al., 2020; McKenzie, 2019; Younes et al., 2020; Zhu et al., 2020). The work presented in

[25] In the context of this chapter, I define one shared micro-mobility service as being *different* from another by distinguishing between the transport modes they offer. Hence, a shared e-scooter service would be different from a shared e-bike service, but two companies offering shared e-scooter services would not qualify as two different shared micro-mobility services.

this thesis hence adds to the literature in that it enables direct comparisons between shared micro-mobility services without accounting for contextual differences between locations.

Second, this thesis estimates the first mode choice models between several different shared micro-mobility services and more established modes of transport. Despite the current policy relevance of shared micro-mobility services and "the issue of mode choice [being] probably the single most important element in transport planning and policy" (Ortúzar and Willumsen, 2011: 207), only one previous study has analysed mode choice between two shared micro-mobility services using stated preference data (Campbell et al., 2016). This thesis adds to the literature in that it demonstrates how to use emerging (revealed preference) data sources such as vehicle and human GPS traces to estimate mode choice models between several different shared micro-mobility services at very high spatiotemporal resolutions. This approach enables the discovery and quantification of particularly important choice attributes for shared micro-mobility services such as access distance and fleet density, which in turn yield valuable insights for operating and regulating shared micro-mobility fleets. This thesis further adds to the literature in that it builds the foundation for incorporating shared micro-mobility services into larger transport simulations in order to estimate their impact at scale and under different policy scenarios.

5.1.4 Outstanding aspects

When reflecting on the research questions posed and the findings provided by this thesis, I find that most research questions have indeed been answered (for Zurich – Section 5.3 discusses the transferability of the results to other cities). Chapter 2 shows how new data sources and methods can be used to advance our understanding of the spatiotemporal differences between different shared micro-mobility services. Chapter 3 analyses user groups of shared micro-mobility services and discusses equity concerns. Finally, Chapter 4 examines the interactions between shared micro-mobility services and more established modes of transport including mode substitution and environmental impacts. One outstanding aspect is the long-term impact of shared micro-mobility services. As these services are still quite new, their long-term impact (e.g., on vehicle ownership) remains unclear. I elaborate this aspect alongside further ideas for future research originating from this thesis in Section 5.4.

5.2 RELEVANCE FOR SOCIETY

One frequently posed question among transport academics and practitioners is: "Should city administrations allow shared micro-mobility services to operate within their jurisdiction?" Here, I offer my reflection on this question taking into account my research along three themes that strike me particularly relevant to future urban transport provision: sustainability, equity and spatial efficiency.

5.2.1 Sustainability

One way to measure the sustainability of transport modes is to elicit its CO_2 emissions. Life-cycle analysis is a particularly comprehensive method to analyse the CO_2 emissions of new transport modes and services as it includes not only CO_2 emissions from energy consumption but also CO_2 emissions from vehicle manufacturing, infrastructure wear and tear, and operational services. Previous studies have consistently shown that the life-cycle CO_2 emissions of current shared micro-mobility services are substantially higher than those of their personally owned counterparts and fall somewhere in the range of public transport (de Bortoli and Christoforou, 2020; Hollingsworth et al., 2019; ITF, 2020a). For Paris, the ITF (2020a) estimates that personal bikes, e-bikes and e-scooters emit 17g, 34g and 42g CO_2 per person kilometre (pkm), respectively, while shared bikes, e-bikes and e-scooters emit 58g, 83g and 106g CO_2 per pkm, respectively. This compares to public transport, which emits between 64g and 91g CO_2 per pkm and private cars, which emit between 124g and 162g CO_2 per pkm (ITF, 2020a).

This picture, however, is incomplete as it assumes that we can compare transport modes side-by-side. When a new transport mode such as shared micro-mobility services enters an established transport system, two processes can be observed. First, the new transport mode *replaces* established transport modes on certain trips. Second, the new transport mode *induces* new trips that otherwise would not have been conducted. Hence, when evaluating the sustainability of a new transport mode by measure of CO_2 emissions, we have to compare the CO_2 emissions of the new transport against the CO_2 emissions of the transport mode mix it replaces and further add the CO_2 emissions of the induced trips. I term the former *gross emissions* and the latter *net emissions* of new transport modes (and services).

Chapter 4 of this thesis extends previous work on life-cycle emissions and trip-based substitution rates of shared micro-mobility services by deriving distance-based substitution rates and calculating net emissions for shared e-bikes and e-scooters. The results indicate that both shared e-bikes and shared e-scooters, on average, emit more CO_2 emissions (83g and 106g per pkm, respectively) than the transport mode mix they replace (52g and 55g per pkm, respectively). These estimates can be regarded as lower ends, as they do not yet account for induced trips.

These results lead me to a first conclusion: current generations of shared dockless e-bikes and shared dockless e-scooters reduce the sustainability of urban transport in Zurich. This conclusion assumes, however, that our findings on substitution rates are representative for users of shared dockless e-bikes and e-scooters, and that life-cycle CO_2 emissions for local service providers are similar to those from the ITF (2020a) study in Paris. At least for shared e-scooters, the companies operating in both cities are similar, which supports our assumption.

A number of comments seem appropriate to place this first conclusion in its larger context. First, generalization to all shared micro-mobility services is not appropriate. Research has shown that different services have different substitution rates and different life-cycle CO_2 emissions. In particular, shared bikes have lower CO_2 emissions than shared e-bikes, and docked e-bike services require less operational services than dockless e-bike services. Second, substitution rates are highly context-dependent. Hence, our results are not generalizable to other cities with different transport systems. Researchers can, however, apply the methods developed in our papers to assess local services within the same framework. Third, our analyses are based on *current* estimates of CO_2 emissions. *Future* estimates are likely to differ as operational services and vehicle lifespans are improved, potentially enough to render some shared micro-mobility services conducive to reduce CO_2 emissions. Correspondingly, the ITF (2020a) already differentiates between first-generation shared e-scooters (122g CO_2 per pkm) and second-generation shared e-scooters (106g CO_2 per pkm).

5.2.2 Equity

Equity in its most general form can be defined as the equivalence of input and output ratios (Adams, 1965; Cook and Hegtvedt, 1983; Walster et al., 1973).

Equity in transport refers to the distribution of costs (input) and benefits (output) across different social groups (Miller, 1999). Transport policy that particularly benefits otherwise disadvantaged social groups is further termed *progressive* with regards to equity, while transport policy that places particular burden on otherwise disadvantaged social groups is termed *regressive* (Litman, 2002).

Progressive transport policy is socially desirable for several reasons. Most importantly, it improves social inclusion by facilitating ways to participate in society for those with otherwise limited options. Low-income population groups, for example, tend to have less and sometimes lower quality transport options available to them than high-income population groups. Less and lower quality transport options in many places imply poorer access to jobs, education, health facilities, and social networks, and is thus one of the main drivers of social exclusion. Improving transport options for those with otherwise limited options, conversely, improves social inclusion.

Income is only one *dimension* of transport equity. Other dimensions frequently applied include gender, education, employment status, caretaker responsibilities, car ownership, ability to move and accessibility of home/work locations (Litman, 2002). Eliciting socio-economic characteristics of user groups of shared micro-mobility services along these dimensions is hence central to understanding whether public investments in dedicated infrastructure (e.g., parking corrals) and redistributions of public space would be *progressive* or *regressive*.

Chapter 3 of this thesis extends previous work on user groups of shared micro-mobility services by providing a comprehensive overview for three different shared micro-mobility services in a single city. Methodologically, we nuance previous discussions by eliciting information on *account holders* and *users*, and by showing that both groups are distinct as a substantial share of account holders is inactive. The results indicate that users of shared micro-mobility services in Zurich indeed share distinctive socio-economic characteristics: they tend to be young, university-educated males with full-time employment living in affluent households without children or cars. This pattern is most pronounced for shared dockless e-bike users and least pronounced for shared dockless e-scooter users. This pattern is further typical for early adopters of new technologies as documented by a wide body of literature (e.g., Black et al., 2001; Li et al., 2008; Lockett and Littler, 1997; Polatoglu and Ekin, 2001; Reinen and

Plomp, 1993; Sulaiman et al., 2007; Morris and Venkatesh, 2000, Wood and Li, 2005).

It is against the backdrop of these results that I offer my second conclusion: users of shared micro-mobility services in Zurich are perhaps the opposite of what one would consider disadvantaged social groups. Hence, equity concerns with regards to public investments in dedicated infrastructure (e.g., parking corrals) and redistributions of public space are justified.

As for the previous topic, this conclusion is drawn based on a *current* snapshot of users of shared micro-mobility services in Zurich. *Future* users could have different socio-economic profiles and there are transport policy options that have the potential to foster inclusiveness. One such example is to ensure equal access to shared micro-mobility services. Today, it is common practice for shared micro-mobility service providers to offer their services in city centres, near universities and in high-income neighbourhoods. City administrations could require shared micro-mobility service providers to reposition their vehicles more broadly and more evenly, for example by measure of population density. Whether such a policy would lead to increased uptake among disadvantaged social groups, however, is questionable as shared micro-mobility services still range among the more expensive transport options in Zurich. Further research is needed.

5.2.3 Spatial efficiency

Shared micro-mobility services are often hailed for their *potential* to save urban space, in particular in comparison to the private car (Figure 11). By definition, it is true that most shared micro-mobility services indeed require less space than most cars both when driven and when parked. What is much less discussed, however, is how much space shared micro-mobility services *actually* save after taking into account empirical substitution rates. What can be assumed on the basis of the research presented in this thesis is that the above case where shared micro-mobility services replace private cars is seldom, at least in Zurich. For most kilometres travelled, shared micro-mobility services replace public transport, cycling or walking, and the potential to save urban space in comparison to these modes is substantially lower. Conducting comprehensive analyses of the net effect of shared micro-mobility services on urban space hence is an important topic for future research.

Figure 11 1 car space = 10 bicycles.

Image source: https://www.construction21.org/articles/h/micromobility-and-car-parking.html

5.2.4 Final remarks

In the preceding subsections, I offered my thoughts on three key themes regarding the larger societal implications of my research. City-administrations aiming to answer the question "Should we allow shared micro-mobility services to operate within our jurisdiction?" may find them useful to determine their own answer, perhaps taking into account additional considerations not reflected on here as the impact of shared micro-mobility services in particular and transport policy objectives in general differ from city to city.

5.3 REFLECTION ON THE PASSAGE OF THE THESIS

In this section, I reflect on early decisions on research design which strike me relevant to share as they have implications for future work.

Most importantly, I decided to conduct the three studies in the same city (Zurich, Switzerland). This decision was driven by opportunistic reasons such as data availability and research funding as well as by my desire to conduct research and to engage with policy makers in a city that I know well. Conducting multiple studies in the same city is beneficial as the role of context is controlled for. Hence, it allows to identify differences in usage, user characteristics and mode choice between different shared micro-mobility services which otherwise might rest obscured by context. Conducting multiple studies in the same city however also has disadvantages. Most importantly, it limits the generalizability of the results. How 'special' is the case of Zurich in its European context? Buehler et al. (2016) systematically compared five European cities (Berlin, Hamburg, Munich, Vienna, Zurich). They found that although the overall population density of Zurich is within the range of the other cities (4200 inhabitants per km^2 compared to 2300-4500 inhabitants per km^2), both the number of public transport trips per capita per year (438 for Zurich compared to 209-318 for the other cities) and the share of households without a car (48% for Zurich compared to 30%-41% for the other cities) substantially differ. These differences can be attributed to the strong focus on public transport provision in recent years in Zurich which has further resulted in a steady mode shift from motorized individual transport to public transport and active modes (Table 16).

Table 16 Trip-based modal split in Zurich.

Transport mode	2000	2005	2010	2015
Walk	26%	26%	27%	26%
Motorized individual transport	40%	36%	30%	25%
Public transport	30%	34%	39%	41%
Bike and e-bike	4%	4%	4%	8%

Source: City of Zurich (2020)
https://www.stadt-zuerich.ch/ted/de/index/taz/verkehr/webartikel/webartikel_kennzahlen_verkehrsentwicklung.html

While bike-sharing services tend to be specific to each country in Europe, the same shared e-scooter companies (e.g., Tier, Voi, Lime, Bird) operate in most European cities. Prices for shared e-scooter trips in all cities are substantially higher than prices for comparable public transport trips. For example, a ten-minute journey with Tier's shared e-scooters in Zurich costs 5 CHF (4.6 EUR), which compares to 2.3 CHF for public transport. In Hamburg, a ten-minute journey with Tier's shared e-scooters costs 2.9 EUR, which compares to 1.8 EUR for public transport.

While some of the results of the studies included in this thesis might hence be specific to Zurich, the methods and approaches proposed to study and to compare the different shared micro-mobility services can be used by researchers regardless of their location. In particular, this applies to Chapter 2 (collecting vehicle data through provider APIs, and reconstructing trips and choice sets) and to Chapter 4 (deriving distance-based substitution rates from mode choice models to calculate net CO_2 emissions).

5.4 FUTURE WORK

Substantial advances in understanding travel behaviour with shared micro-mobility services have been made in recent years. It goes without saying that further promising areas for future research exist. Here, I elucidate four that warrant particular attention going forward in addition to the ones articulated in the previous section.

First, this thesis has shown how to use emerging data sources such as vehicle and human GPS traces to understand travel behaviour at high spatiotemporal resolutions. At the moment, however, multiple matching data sets, i.e. GPS traces and booking data for every mode, are necessary as automatic mode detection usually fails with shared micro-mobility services (e.g., private bikes cannot be differentiated from bikesharing). Going forward, mode detection algorithms could be improved by exploiting systematic differences between shared and private modes based on logic (e.g., docking stations, incomplete tours) as well as automated pattern recognition.

Second, human GPS tracks, once widely available with correct labels for shared micro-mobility services, can be used to gain a deeper understanding of their intermodal use. First and last miles to and from public transport stations are of particular interest to understand whether and how shared micro-mobility services increase the catchment area of public transport.

Third, this thesis has explored some of the short-term impacts of shared micro-mobility services (e.g., on mode choice) and their implications for the sustainability of urban transport. Long-term impacts of shared micro-mobility services (e.g., on vehicle ownership) might be even more important yet remain understudied. For example, my research shows that personal e-bikes are used more sustainably (e.g., replace cars on commutes) than shared e-bikes. Shared e-bikes, however, enable users to try e-bikes without upfront capital investment and could thereby spark long-term sustainable mobility transitions despite their short-term negative impact on sustainability. Longitudinal research is needed to collect and model evidence on uptake, usage and long-term effects of shared micro-mobility services on vehicle ownership in the years to come.

Last but not least, this thesis explored mode choice between shared micro-mobility services and more established urban transport modes. Incorporating our results into transport simulations such as MATSim (Horni et al., 2016), for example using the well-established Zurich scenario, would allow for estimation of their impact at different organizational configurations (e.g., single or multiple providers), at different fleet sizes, and under varying policy scenarios.

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APPENDIX

A.1 UTILITY FUNCTIONS

We specify the utility functions for the mixed logit model using the abbreviations as follows:

<u>Modes</u>

WA	Walk
PT	Public transport
CA	Car
BI	Bike
PEB	Private e-bike
SEB	Shared e-bike
PES	Private e-scooter
SES	Shared e-scooter

<u>Attributes</u>

DI	Trip distance
AD	Access distance
TR	Transfers
EL	Elevation
MO	Morning
NI	Night
PR	Precipitation
WI	Wind
PTL	PT season ticket (local)
PTC	PT season ticket (nation)
PTB	PT season ticket (bundle)
HHC	Cars in household
HHB	Bikes in household
HHE	E-bikes in household
HHS	E-scooters in household
UE	University education
FT	Full-time employment
AG	Age
FE	Female

<u>Utility functions</u>

$$U_{WA} = ASC_{WA}$$

$$U_{PT} = ASC_{PT} + \beta_{PT_{DI}} * DI + \beta_{PT_{DI2}} * DI^2 + \beta_{PT_{PRDI}} * PR * DI + \beta_{PT_{AD}} * AD + \beta_{PT_{TR}} * TR + \beta_{PT_{PTB}} * PTB + \beta_{PT_{PTL}} * PTL + \beta_{PT_{PTC}} * PTC$$

$$U_{CA} = ASC_{CA} + \beta_{CA_{DI}} * DI + \beta_{CA_{DI2}} * DI^2 + \beta_{CA_{PRDI}} * PR * DI + \beta_{CA_{HHC}} * HHC$$

$$U_{BI} = ASC_{BI} + \beta_{BI_{DI}} * DI + \beta_{BI_{DI2}} * DI^2 + \beta_{BI_{PRDI}} * PR * DI + \beta_{BI_{HHB}} * HHB + \beta_{BI_{WI}} * WI * DI + \beta_{BI_{EL}} * EL * DI$$

$$U_{PEB} = ASC_{PEB} + \beta_{PEB_{DI}} * DI + \beta_{PEB_{DI2}} * DI^2 + \beta_{PEB_{PRDI}} * PR * DI + \beta_{PEB_{HHE}} * HHE + \beta_{PEB_{MO}} * MO + \beta_{PEB_{NI}} * NI$$

$$U_{SEB} = ASC_{SEB} + \beta_{SEB_{DI}} * DI + \beta_{SEB_{DI2}} * DI^2 + \beta_{SEB_{PRDI}} * PR * DI + \beta_{SEB_{PTB}} * PTB + \beta_{SEB_{AD}} * AD + \beta_{SEB_{MO}} * MO + \beta_{SEB_{NI}} * NI + \beta_{SEB_{AG}} * AG + \beta_{SEB_{FE}} * FE + \beta_{SEB_{UE}} * UE + \beta_{SEB_{FT}} * FT$$

$$U_{PES} = ASC_{PES} + \beta_{PES_{DI}} * DI + \beta_{PES_{DI2}} * DI^2 + \beta_{PES_{PRDI}} * PR * DI + \beta_{PES_{HHS}} * HHS + \beta_{PES_{MO}} * MO + \beta_{PES_{NI}} * NI$$

$$U_{SES} = ASC_{SES} + \beta_{SES_{DI}} * DI + \beta_{SES_{DI2}} * DI^2 + \beta_{SES_{PRDI}} * PR * DI + \beta_{SES_{PTB}} * PTB + \beta_{SES_{AD}} * AD + \beta_{SES_{MO}} * MO + \beta_{SES_{NI}} * NI + \beta_{SES_{AG}} * AG + \beta_{SES_{FE}} * FE + \beta_{SES_{UE}} * UE + \beta_{SES_{FT}} * FT$$

Note that all alternative specific constants are random to account for taste heterogeneity in mode choice between individuals.

A.2 SURVEY (GERMAN VERSION)

Beginn des Blocks: Willkommen

Willkommen bei unserer Mobilitätsstudie und vielen Dank, dass Sie mitmachen! Alle Ihre Angaben werden streng vertraulich behandelt. Sie dienen ausschliesslich Forschungszwecken und statistischen Auswertungen. Alle mit der Erhebung beschäftigten Personen sind zur Verschwiegenheit verpflichtet. Bei Fragen stehen wir Ihnen gerne unter [email address] zur Verfügung.

Ende des Blocks: Willkommen

Beginn des Blocks: Teilnahmevoraussetzungen

Damit Sie an dieser Studie teilnehmen können, müssen Sie

- einen Führerschein der Kategorie B1 (Pkw) besitzen,
- ein Smartphone (mit Betriebssystem Apple iOS oder Android) besitzen,
- in der Schweiz wohnen sowie sich regelmässig in der Stadt Zürich aufhalten.

○ Ja, ich erfülle diese Voraussetzungen.

○ Nein, ich erfülle diese Voraussetzungen nicht.

Ende des Blocks: Teilnahmevoraussetzungen

Beginn des Blocks: Informationen zur Studie

Bevor Sie mit dem Ausfüllen des Fragebogens beginnen, möchten wir Sie bitten, sich die Informationen zur Studie aufmerksam durchzulesen und anschliessend die folgende Einverständniserklärung zu akzeptieren:

- Ich nehme an dieser Studie freiwillig teil und kann jederzeit ohne Angabe von Gründen meine Zustimmung zur Teilnahme widerrufen,

ohne dass mir deswegen Nachteile entstehen. Die Belohnung zur vollständigen Teilnahme wird in diesem Fall hinfällig.
- Ich wurde schriftlich über die Ziele, den Ablauf der Studie, über mögliche Vor- und Nachteile sowie über eventuelle Risiken informiert.
- Ich habe die zur oben genannten Studie angegebenen Informationen zur Studie gelesen. Meine Fragen im Zusammenhang mit der Teilnahme an dieser Studie sind mir zufriedenstellend beantwortet worden.
- Ich hatte genügend Zeit, um meine Entscheidung zu treffen.
- Ich bin einverstanden, dass die zuständigen Untersuchenden und/oder Mitglieder der Ethikkommission zu Prüf- und Kontrollzwecken meine Originaldaten einsehen dürfen, jedoch unter strikter Einhaltung der Vertraulichkeit.

○ Ja, ich möchte mit der Studie beginnen.

○ Nein, ich möchte nicht an der Studie teilnehmen.

Ende des Blocks: Informationen zur Studie

Beginn des Blocks: Identifikation

Bitte geben Sie Ihren Vor- und Nachnamen an.

○ Vorname ________________________________

○ Nachname ________________________________

Bitte geben Sie Ihre E-Mail-Adresse an (diese brauchen wir, um Ihnen die Anleitung für den weiteren Studienverlauf zukommen zu lassen)

____

Bitte geben Sie Ihre E-Mail-Adresse erneut an (Validierung)

____

Ende des Blocks: Identifikation

Beginn des Blocks: Haushalt

Um Ihre Antworten besser interpretieren zu können, bitten wir Sie im Folgenden um allgemeine Angaben zu Ihrem Haushalt.

Bitte geben Sie die Adresse Ihres (Haupt-) Wohnortes an.

○ Strasse ____

○ Hausnummer ____

○ Postleitzahl ____

○ Ort ____

Haben Sie einen Zweitwohnort?

○ Ja

○ Nein

Wie viele Personen wohnen in Ihrem (Haupt-) Haushalt mindestens 4 Tage pro Woche? (Sie selbst mit einbezogen)

	0	1	2	3	4	5	> 5
Kleinkinder (< 6 Jahre)	○	○	○	○	○	○	○
Kinder (6-12 Jahre)	○	○	○	○	○	○	○
Jugendliche (13-18 Jahre)	○	○	○	○	○	○	○
Erwachsene (> 18 Jahre)	○	○	○	○	○	○	○

Welcho Situation beschreibt Ihren Haushalt am besten?

- ○ Ich wohne gemeinsam mit meinem Partner*in.
- ○ Ich wohne in einer Wohngemeinschaft (WG).
- ○ Andere ____

Wie hoch ist das monatliche Bruttototaleinkommen des gesamten Haushalts? (Summe in CHF von allen Haushaltsmitgliedern)

Das Haushaltseinkommen ist eine der wichtigsten Variablen in der Verkehrsforschung. Dazu gehören alle Erwerbseinkommen, alle Kapitalerträge wie z.B. Zinsen, Aktien oder Mieteinnahmen, aber auch alle staatlichen und privaten Renten oder Zuschüsse wie z.B. AHV, Arbeitslosenunterstützung, IV, Sozialhilfe, Stipendien, Unterhaltsbeiträge, etc. Wenn Sie in einer WG wohnen, bitten wir Sie, Ihr persönliches Brutto-Einkommen anzugeben.

- ○ Kein Einkommen
- ○ Weniger als 2'000
- ○ 2'001 - 4'000
- ○ 4'001 - 6'000
- ○ 6'001 - 8'000
- ○ 8'001 - 10'000
- ○ 10'001 - 12'000
- ○ 12'001 - 14'000
- ○ 14'001 - 16'000
- ○ Mehr als 16'000
- ○ Keine Angabe

Haben Sie Hunde in Ihrem Haushalt?

- ◯ Ja
- ◯ Nein

Wie viele der folgenden Verkehrsmittel besitzt Ihr Haushalt? (Dazu zählen auch ständig zur Verfügung stehende Geschäfts- und Dienstautos)

	0	1	2	3	4	5	> 5
Auto	◯	◯	◯	◯	◯	◯	◯
Motorrad / Roller	◯	◯	◯	◯	◯	◯	◯
Velo	◯	◯	◯	◯	◯	◯	◯
E-Bike	◯	◯	◯	◯	◯	◯	◯
E-Trottinett	◯	◯	◯	◯	◯	◯	◯
Anderes Verkehrsmittel	◯	◯	◯	◯	◯	◯	◯

Planen Sie in den kommenden 3 Monaten Änderungen an Ihrem Bestand an Verkehrsmitteln?

- ◯ Ja
- ◯ Nein

Was haben Sie vor?

	reduzieren	ersetzen	erweitern	keine Änderung
Auto	○	○	○	○
Motorrad / Roller	○	○	○	○
Velo	○	○	○	○
E-Bike	○	○	○	○
E-Trottinett	○	○	○	○

Warum wollen Sie diese Änderung durchführen?

____

Ende des Blocks: Haushalt

Beginn des Blocks: Person

Im folgenden Abschnitt geht es um Ihre persönlichen Angaben.

In welchem Jahr sind Sie geboren?

○ ________________________________

Sind Sie ...

○ weiblich?

○ männlich?

○ divers?

Welche Staatsbürgerschaft haben Sie? (Doppelbürger/innen kreuzen bitte beide an)

- ◯ Schweizer/-in
- ◯ Andere, und zwar ____
- ◯ Weitere, und zwar ____

Sind Sie aufgrund einer Krankheit, Behinderung oder sonstigen physischen Einschränkung nicht in der Lage, eines oder mehrere der folgenden Verkehrsmittel zu verwenden? (Mehrere Antworten möglich)

- ◯ Nein, keine Einschränkung
- ◯ Auto (als Fahrer*in)
- ◯ Öffentlicher Verkehr
- ◯ Fahrrad
- ◯ Zu Fuss

Was ist Ihr höchster Ausbildungsabschluss?

- ◯ Obligatorische Schule
- ◯ Weiterführende Ausbildung (Lehre, Berufsschule, Matura, etc.)
- ◯ Universität / Technische Hochschule, Fachhochschule

Besitzen Sie ein Smartphone?

- ◯ Ja
- ◯ Nein

Ende des Blocks: Person

Beginn des Blocks: Beschäftigung

Wie ist Ihr derzeitiger Beschäftigungsstatus? Sie sind...
(Mehrere Antworten möglich)

- ○ berufstätig
- ○ in Ausbildung
- ○ im eigenen Haushalt beschäftigt
- ○ auf Arbeitssuche
- ○ nicht erwerbstätig
- ○ pensioniert
- ○ Invalid (z.B. IV-Bezüger/in)
- ○ im Militär / Zivildienst
- ○ Sonstiges: ____

Haben Sie einen (Haupt-) Arbeits-/ Ausbildungsort?

- ○ Ja
- ○ Nein

Bitte geben Sie die Adresse Ihres (Haupt-) Arbeits-/ Ausbildungsortes an.

- ○ Arbeitgeber / Ausbildungsort ________________________
- ○ Strasse ____
- ○ Hausnummer ____________________________________
- ○ Postleitzahl ____________________________________
- ○ Ort ____

Ende des Blocks: Beschäftigung

Beginn des Blocks: Beschäftigung : berufstätig

Sie haben angegeben, dass Sie derzeitig "beschäftigt" sind. Bitte beantworten Sie die nachfolgenden Fragen dazu.

Sind Sie...

○ angestellt?

○ selbstständig?

Welche Art von Beschäftigung führen Sie aus?

○ Vollzeitbeschäftigung (80-100%)

○ Eine Teilzeitbeschäftigung

○ Mehr als eine Teilzeitbeschäftigung

Haben Sie derzeit regelmässige Arbeitszeiten?

○ Ja

○ Nein

Arbeiten Sie derzeit in Schichten?

○ Ja

○ Nein

Sind Sie Berufsfahrer*in? (z.B. Taxifahrer*in, Zugführer*in, Busfahrer*in, Strassenbahnfahrer*in, Auslieferungsfahrer*in)

○ Ja

○ Nein

Ende des Blocks: Beschäftigung : berufstätig

Beginn des Blocks: Beschäftigung : in Ausbildung

Sie haben angegeben, dass Sie derzeitig "in Ausbildung" sind. Bitte beantworten Sie die nachfolgende Frage dazu.

Sind Sie ...

- ◯ Schüler*in?
- ◯ In Berufsausbildung?
- ◯ Student*in?
- ◯ Doktorand*in?
- ◯ Andere ____

Ende des Blocks: Beschäftigung : in Ausbildung

Beginn des Blocks: COVID-19

Unser Alltag hat sich in den letzten Monaten aufgrund der COVID-19 Pandemie z.T. drastisch verändert. Diese Fragen versuchen diese Veränderungen zu erfassen und beziehen sich auf Ihren Alltag in den letzten 7 Tagen.

Sind Sie aktuell in Kurzarbeit?

- ◯ Ja
- ◯ Nein

Ist Ihr regulärer Arbeitsplatz ausserhalb Ihrer Wohnung?

○ Ja

○ Nein

An wie vielen Tagen arbeiteten Sie an Ihrem regulären Arbeitsplatz?

○ ____

An wie vielen Tagen arbeiteten Sie zu Hause im Home-Office?

○ ____

Ende des Blocks: COVID-19

Beginn des Blocks: Mobilität : Einführung

In den folgenden Fragen geht es um persönliche Angaben zu Ihrer Mobilität.

Von welchen dieser «neuen» Verkehrsmittel haben Sie schon einmal gehört? (Bitte alle zutreffenden ankreuzen)

○ E-Bike

○ E-Trottinett

Von welchen dieser «neuen» Mobilitätsdienstleistungen haben Sie schon einmal gehört? (Bitte alle zutreffenden ankreuzen)

○ Carsharing (z.B. Mobility, Catch a Car)

○ (E-)Bikesharing (z.B. PubliBike, Smide / Bond, Pick-e-Bike)

○ E-Trottinett Sharing (z.B. Bird, Lime, Tier, Voi)

○ Uber

Sie kennen eine oder mehrere neue Verkehrsmittel / Mobilitätsdienstleistungen nicht. Hier eine kurze Einführung.

«Neue Verkehrsmittel»

- E-Bikes sind Velos mit einem elektrischen Hilfsmotor.
- E-Trottinetts ähneln Tretrollern, werden aber elektrisch betrieben. Sie haben i.d.R. keinen Sitz.

«Neue Mobilitätsdienstleistungen»

- Carsharing (z.B. Mobility, Catch a Car) ermöglicht ein kurzzeitiges, auch minutenweises Anmieten von Fahrzeugen.
- (E-)Bikesharing (z.B. PubliBike, Smide / Bond, Pick-e-Bike) ermöglicht ein kurzfristiges, auch minutenweises Anmieten von Velos / E-Bikes.
- E-Trottinett Sharing ermöglicht ein kurzfristiges, auch minutenweises Anmieten von E-Trottinetts
- Uber ist ein Fahrdienst für Personenbeförderung, ähnlich zu Taxiunternehmen.

Ende des Blocks: Mobilität : Einführung

Beginn des Blocks: Mobilität : Verfügbarkeit

Bei welchen der folgenden Angebote sind Sie aktuell Mitglied bzw. Nutzer? (Bitte kreuzen Sie alle zutreffenden an)

- ○ Mobility Carsharing (inkl. Catch a Car)
- ○ Mitfahrzentrale / Mitfahrgelegenheit / BlaBlaCar
- ○ Uber
- ○ PubliBike
- ○ Smide / Bond
- ○ Pick-e-Bike
- ○ Tier
- ○ Voi
- ○ Lime
- ○ Bird
- ○ Andere ____________________

Welche der folgenden Mitgliedschaften bei «PubliBike» haben Sie?

- ○ QuickBike (keine Monats-/Jahresgebühr)
- ○ EasyBike (erste 30 min Velo gratis)
- ○ FreeBike (erste 30 Min Velo & E-Bike gratis)
- ○ Andere ____________________

Welche der folgenden Mitgliedschaften bei «Smide / Bond» haben Sie?

- ○ Keine (ich nutze Smide / Bond und bezahle den regulären Preis)
- ○ Halbtax (50% auf jede Fahrt)
- ○ Easy (täglich 6 km kostenlos)
- ○ Premium (täglich 30 km kostenlos)
- ○ Andere ____________________

Besitzen Sie einen in der Schweiz gültigen Führerausweis für Personenwagen? (Kategorie B1)

- ○ Ja
- ○ Nein

Wie oft steht Ihnen ein Auto zur Verfügung?

Gemeint sind eigene Autos oder Autos, die Sie kurzfristig z.B. von Bekannten / Freunden ausleihen können, nicht aber Mietwagen oder Carsharing.

- ○ Immer
- ○ Häufig
- ○ Selten / nach Absprache
- ○ Nie

Welche der folgenden Verkehrsmittel und Mobilitätsdienstleistungen sind an Ihrem (Haupt-) Wohnort verfügbar? (Bitte kreuzen Sie alle zutreffenden an)

- ○ Carsharing (z.B. Mobility, Catch a Car)
- ○ (E-)Bikesharing (z.B. PubliBike, Smide / Bond, Pick-e-Bike)
- ○ E-Trottinett Sharing (z.B. Voi, Lime, Bird, Tier)
- ○ Uber
- ○ Öffentlicher Verkehr

Welche der folgenden Verkehrsmittel sind an Ihrem (Haupt-) Arbeits-/ Ausbildungsort verfügbar? (Bitte kreuzen Sie alle zutreffenden an)

- ◯ Carsharing (z.B. Mobility, Catch a Car)
- ◯ (E-)Bikesharing (z.B. PubliBike, Smide / Bond, Pick-e-Bike)
- ◯ E-Trottinett Sharing (z.B. Voi, Lime, Bird, Tier)
- ◯ Uber
- ◯ Öffentlicher Verkehr

Wie zufrieden sind Sie mit der ÖV-Anbindung an Ihrem...

	Überhaupt nicht zufrieden				Voll und ganz zufrieden
	0	25	50	75	100
(Haupt-) Wohnort?					
(Haupt-) Arbeits-/ Ausbildungsort					

Ende des Blocks: Mobilität : Verfügbarkeit

Beginn des Blocks: Mobilität : Arbeits-/ Ausbildungsweg

Welche(s) Verkehrsmittel nutzen Sie normalerweise (d.h. vor / nach der COVID-19 Pandemie), um von Ihrem (Haupt-) Wohnort zu Ihrem (Haupt-) Arbeits-/ Ausbildungsort zu kommen? (Bitte kreuzen Sie alle zutreffenden an)

○ Zu Fuss

○ Velo

○ E-Bike

○ E-Trottinett

○ Auto

○ Motorrad / Roller

○ Öffentlicher Verkehr

○ Anderes Verkehrsmittel: ________________________________

Fahren Sie diese Strecke in der Regel alleine?

○ Ja

○ Nein

Verfügen Sie an Ihrem Arbeits- bzw. Ausbildungsort über einen Parkplatz?

○ Ja

○ Nein

Ende des Blocks: Mobilität : Arbeits-/ Ausbildungsweg

Beginn des Blocks: Mobilität : Verkehrsmittelnutzung

Wie häufig nutzen Sie aktuell die folgenden Verkehrsmittel?

	(nahezu) täglich	mehrfach pro Woche	mehrfach pro Monat	seltener / nie
Auto	○	○	○	○
Öffentlicher Verkehr	○	○	○	○
Uber / Taxi	○	○	○	○
Motorrad / Roller	○	○	○	○
Velo	○	○	○	○
E-Bike	○	○	○	○
E-Trottinett	○	○	○	○

Planen Sie für die nächsten 3 Monate Änderungen an der Häufigkeit Ihrer Verkehrsmittelnutzung?

○ Ja

○ Nein

Was haben Sie vor?

	seltener nutzen	keine Änderung	häufiger nutzen
Auto	○	○	○
Öffentlicher Verkehr	○	○	○
Uber / Taxi	○	○	○
Motorrad / Roller	○	○	○
Velo	○	○	○
E-Bike	○	○	○
E-Trottinett	○	○	○

Ende des Blocks: Mobilität : Verkehrsmittelnutzung

Beginn des Blocks: Mobilität : ÖV

Verfügen Sie aktuell über ein oder mehrere ÖV-Abonnements? (Bitte kreuzen Sie alle zutreffenden an)

○ GA (1. Klasse)

○ GA (2. Klasse)

○ Halbtax Abonnement

○ Verbund Abonnement (z.B. ZVV Netzpass, U-Abo, Libero-Abo, Tarifverbund Nord-Westschweiz (TNW))

○ Strecken Abonnement

○ Mehrfahrtenkarte

○ Seven 25

○ Andere ____

Wird Ihnen eines oder mehrere Ihrer Abonnements von Ihrem Arbeitgeber zur Verfügung gestellt oder teilweise mitfinanziert?

○ Ja

○ Nein

Planen Sie in den kommenden 3 Monaten Änderungen an Ihrem Bestand an ÖV-Abonnements?

○ Ja

○ Nein

Was haben Sie vor?

	kündigen / nicht verlängern	keine Änderung	(weiteres) kaufen
GA (1. Klasse)	○	○	○
GA (2. Klasse)	○	○	○
Halbtax Abonnement	○	○	○
Verbund Abonnement	○	○	○
Strecken Abonnement	○	○	○
Mehrfahrtenkarte	○	○	○
Seven 25	○	○	○
Andere	○	○	○

Ende des Blocks: Mobilität : ÖV

Beginn des Blocks: Mobilität : E-Trottinett

Die folgenden Fragen beziehen sich auf Ihre letzte Fahrt mit einem E-Trottinett.

Wann haben Sie Ihre letzte Fahrt mit einem E-Trottinett unternommen?

○ In den letzten 7 Tagen

○ Die letzte Fahrt liegt mehr als 7 Tage zurück

○ Ich bin noch nie E-Trottinett gefahren

Zu welcher Tageszeit haben Sie diese Fahrt unternommen?

- ○ Unter der Woche: Morgens
- ○ Unter der Woche : Mittags
- ○ Unter der Woche : Abends
- ○ Unter der Woche : Nachts
- ○ Am Wochenende : Morgens
- ○ Am Wochenende : Mittags
- ○ Am Wochenende : Abends
- ○ Am Wochenende : Nachts

Wie viele Minuten hat diese Fahrt gedauert?

- ○ unter 5 min
- ○ zwischen 5 und 10 min
- ○ zwischen 10 und 15 min
- ○ länger als 15 min

Haben Sie das E-Trottinett für die Fahrt gemietet (z.B. über Bird / Lime / Voi / Tier) oder besitzen Sie es selbst?

- ○ Gemietet
- ○ Eigenes

Was war das Ziel dieser Fahrt?

- ○ Fahrt zur Arbeits- oder Ausbildungsstätte
- ○ Fahrt zum Restaurant / Bar
- ○ Fahrt zu/von einer ÖV Haltestelle
- ○ Fahrt nach Hause
- ○ Freizeitaktivitäten
- ○ Einkaufen / Besorgungen
- ○ Besuch von Freunden und Familie
- ○ Anderes Ziel ______________________________

Warum haben Sie ein E-Trottinett als Verkehrsmittel gewählt? (Mehrere Antworten möglich)

- ○ Es ist schnell.
- ○ Es macht Spass.
- ○ Es ist günstig.
- ○ Zum Ausprobieren.
- ○ Anderer Grund ______________________________

Hätten Sie die Fahrt auch unternommen, wenn kein E-Trottinett zur Verfügung gestanden hätte?

- ○ Ja
- ○ Nein

Welches alternative Verkehrsmittel hätten Sie gewählt?

- ◯ Zu Fuss
- ◯ Velo
- ◯ E-Bike
- ◯ Auto
- ◯ Öffentlicher Verkehr
- ◯ Carsharing
- ◯ Uber
- ◯ Taxi
- ◯ Motorrad / Roller

Ende des Blocks: Mobilität : E-Trottinett

Beginn des Blocks: Prioritäten und Einstellungen

Was sind Ihre generellen Prioritäten beim Reisen?

	Unwichtig	Eher unwichtig	Eher wichtig	Wichtig	Keine Angabe
Preis	◯	◯	◯	◯	◯
Flexibilität	◯	◯	◯	◯	◯
Komfort	◯	◯	◯	◯	◯
Zeit	◯	◯	◯	◯	◯
Umwelt	◯	◯	◯	◯	◯

Ende des Blocks: Prioritäten und Einstellungen

Vielen Dank für das Ausfüllen des ersten Fragebogens. Gerne schicken wir Ihnen nun Informationen zum zweiten Teil der Studie, dem Mobilitätstagebuch, zu.

A.3 SURVEY (ENGLISH VERSION)

Beginning of the block: Welcome

Welcome to our mobility study and thank you for participating! All your information will be treated with the strictest confidence. It will be used exclusively for research purposes and statistical evaluations. If you have any questions, please do not hesitate to contact us at [email address].

End of the block: Welcome

Beginning of the block: Participation requirements

In order to participate in this study, you must

- have a driving license of category B1 (car),
- have a smartphone (with Apple iOS or Android operating system),
- live in Switzerland and regularly reside in the city of Zurich.

○ Yes, I meet these requirements.

○ No, I do not meet these requirements.

End of the block: Participation requirements

Beginning of the block: Information about the study

Before you start to fill out the questionnaire, we would like to ask you to read the information on the study carefully and to accept the following declaration of consent:

- I take part in this study voluntarily and can revoke my consent to participate at any time without giving reasons and without incurring any disadvantages. In this case, the reward is void.
- I was informed in writing about the goals, the course of the study, possible advantages and disadvantages as well as possible risks.
- I have read the information on the study. My questions on participating in this study have been answered satisfactorily.
- I have had enough time to make my decision.
- I agree that the responsible investigators and / or members of the ethics committee may review my data for controlling purposes subject to strict confidentiality.

○ Yes, I want to start the study.

○ No, I do not want to take part in the study.

End of the block: Information about the study

Beginning of the block: Identification

Please enter your first and last name.

○ First name ____

○ Last name ____

Please enter your e-mail address (we need this to send you instructions on the due course of the study)

____

Please enter your email address again (validation)

____

End of the block: Identification

Beginning of the block: Household

In order to be able to interpret your answers better, we ask you below for general information about your household.

Please enter the address of your (main) place of residence.

- ○ Street name ____
- ○ House number ____
- ○ Post code ____
- ○ Town ____

Do you have a second place of residence?

- ○ Yes
- ○ No

How many people live in your (main) household at least 4 days a week? (yourself included)

	0	1	2	3	4	5	> 5
Infants (< 6 years)	○	○	○	○	○	○	○
Children (6-12 years)	○	○	○	○	○	○	○
Adolescents (13-18 years)	○	○	○	○	○	○	○
Adults (> 18 years)	○	○	○	○	○	○	○

Which situation best describes your household?

- ○ I live with my partner.
- ○ I live in a shared flat.
- ○ Other ____

What is the total monthly gross income of the entire household? (sum in CHF from all household members)

Household income is one of the most important variables in transportation research. This includes all earnings, all investment income such as interests, shares or rental income, but also all state and private pensions or grants such as AHV, unemployment benefits, IV, social assistance, scholarships, maintenance contributions, etc. If you live in a shared flat, please indicate your personal gross income.

- ○ No income
- ○ Less than 2'000
- ○ 2'001 - 4'000
- ○ 4'001 - 6'000
- ○ 6'001 - 8'000
- ○ 8'001 - 10'000
- ○ 10'001 - 12'000
- ○ 12'001 - 14'000
- ○ 14'001 - 16'000
- ○ More than 16'000
- ○ No information

Are there any dogs in your household?

- ○ Yes
- ○ No

How many of the following modes of transport does your household have? (This also includes business and company cars that are always available)

	0	1	2	3	4	5	> 5
Auto	○	○	○	○	○	○	○
Motorcycle/ scooter	○	○	○	○	○	○	○
Bike	○	○	○	○	○	○	○
E-Bike	○	○	○	○	○	○	○
E-Scooter	○	○	○	○	○	○	○
Other modes of transport	○	○	○	○	○	○	○

Do you plan to make any changes to your transport inventory in the next 3 months?

○ Yes

○ No

What do you plan to do?

	reduce	replace	expand	no change
Auto	◯	◯	◯	◯
Motorbike / scooter	◯	◯	◯	◯
Bike	◯	◯	◯	◯
E-Bike	◯	◯	◯	◯
E-Scooter	◯	◯	◯	◯

Why do you want to make this change?

____

End of the block: Household

Beginning of the block: Person

The following section concerns your person.

Which year were you born in?

◯ ____

Do you identify as ...

◯ female?

◯ male?

◯ other?

What is your citizenship? (dual citizens please list both)

- ◯ Swiss
- ◯ Other ____
- ◯ Further ____

Are you unable to use one or more of the following modes of transport due to an illness, disability or other physical limitation? (Multiple answers possible)

- ◯ No restriction
- ◯ Car (as driver)
- ◯ Public transport
- ◯ Bike
- ◯ Foot

What is your highest level of educational attainment?

- ◯ Compulsory school
- ◯ Further education (e.g., mature, apprenticeship, vocational school)
- ◯ University

Do you own a smartphone? (Apple or Android)

- ◯ Yes
- ◯ No

End of the block: Person

Beginning of the block: Occupation

What is your current occupation? (multiple answers possible))

- ○ employed
- ○ in training
- ○ working in own household
- ○ looking for employment
- ○ unemployed
- ○ retired
- ○ disabled (e.g., IV recipient)
- ○ in the military / civil service
- ○ other: ____

Do you have a (main) place of work / training?

- ○ Yes
- ○ No

Please enter the address of your (main) place of work / training.

- ○ Name of employer / institution ______________________________
- ○ Street name ____
- ○ House number ____
- ○ Post code ____
- ○ Town ____

End of the block: Occupation

Beginning of the block: Occupation: employed

You indicated that you are currently "employed". Please answer the following questions.

Are you...

- ◯ employed?
- ◯ self-employed?

What kind of occupation do you follow?

- ◯ One full-time employment (80-100%)
- ◯ One part-time employment
- ◯ More than one part-time employments

Do you have regular working hours?

- ◯ Yes
- ◯ No

Do you work in shifts?

- ◯ Yes
- ◯ No

Are you a professional driver? (e.g. taxi driver, train driver, bus driver, tram driver, delivery driver)

- ◯ Yes
- ◯ No

End of the block: Occupation: employed

Beginning of the block: Occupation: in training

You indicated that you are currently "in training". Please answer the following question.

Are you...

- ◯ a school student?
- ◯ a university student?
- ◯ a doctoral student?
- ◯ in vocational training?
- ◯ Other ________________________________

End of the block: Occupation: in training

Beginning of the block: COVID-19

Everyday life has drastically changed due to the COVID-19 pandemic. These questions try to capture these changes and relate to your everyday life in the last 7 days.

Do you currently work short-time?

- ◯ Yes
- ◯ No

Is your regular workplace outside of your home?

- ◯ Yes
- ◯ No

How many days did you work at your regular workplace in the past week?

○ ____

How many days did you work from home in the home office in the past week?

○ ____

End of the block: COVID-19

Beginning of the block: Mobility: Introduction

Which of the following "new" modes of transport have you heard of? (please tick all that apply)

○ E-Bike

○ E-Scooter

Which of these "new" mobility services have you heard of? (please tick all that apply)

○ Carsharing (e.g., Mobility, Catch a Car)

○ (E-)Bikesharing (e.g., PubliBike, Smide / Bond, Pick-e-Bike)

○ E-Scooter Sharing (e.g., Bird, Lime, Tier, Voi)

○ Uber

You are not familiar with one or more new means of transport / mobility services. Here is a brief introduction.

"New means of transport"

- E-Bikes are bicycles with an electric motor.
- E-Scooters are similar to kick-scooters, but with an electric motor. They do not have a seat.

"New mobility services"

- Car sharing (e.g., Mobility, Catch a Car) allows short-term rental of vehicles.
- (E-)bike sharing (e.g., PubliBike, Smide / Bond, Pick-e-Bike) allows short-term rental of bicycles / e-bikes.
- E-Scooter sharing allows short-term rental of e-scooters.
- Uber is a passenger transport service similar to taxis.

End of the block: Mobility: Introduction

Beginning of the block: Mobility: Availability

Which of the following services do you use or do you have an account with? (please tick all that apply)

- ○ Mobility Carsharing (incl. Catch a Car)
- ○ Mitfahrzentrale / Mitfahrgelegenheit / BlaBlaCar
- ○ Uber
- ○ PubliBike
- ○ Smide / Bond
- ○ Pick-e-Bike
- ○ Tier
- ○ Voi
- ○ Lime
- ○ Bird
- ○ Other ____

Which of the following memberships do you have with "PubliBike"?

- ○ QuickBike (no monthly / yearly fee)
- ○ EasyBike (first 30 min with a bike for free)
- ○ FreeBike (first 30 min with a bike or e-bike for free)
- ○ Other ____

Which of the following memberships do you have with "Smide / Bond"?

- ○ None (I use Smide / Bond and pay the regular prie)
- ○ Halbtax (50% on every trip)
- ○ Easy (daily 6 km included)
- ○ Premium (daily 30 km included)
- ○ Other ____

Do you have a driver's license for cars that is valid in Switzerland? (Category B1 or similar)

- ○ Yes
- ○ No

How often is a car available to you?

This refers to your own cars or cars that you can borrow from acquaintances / friends at short notice, but not rental cars or car sharing.

- ○ Always
- ○ Often
- ○ Rarely / by arrangement
- ○ Never

Which of the following modes of transport and mobility services are available at your (main) place of residence? (Please tick all that apply)

- ○ Carsharing (e.g., Mobility, Catch a Car)
- ○ (E-)Bikesharing (e.g., PubliBike, Smide / Bond, Pick-e-Bike)
- ○ E-Scooter Sharing (e.g., Voi, Lime, Bird, Tier)
- ○ Uber
- ○ Public transport

Which of the following modes of transport and mobility services are available at your (main) place of work / training? (Please tick all that apply)

- ◯ Carsharing (e.g., Mobility, Catch a Car)
- ◯ (E-)Bikesharing (e.g., PubliBike, Smide / Bond, Pick-e-Bike)
- ◯ E-Scooter Sharing (e.g., Voi, Lime, Bird, Tier)
- ◯ Uber
- ◯ Public transport

How satisfied are you with public transport at your...

	Totally unsatisfied 0	25	50	75	Totally satisfied 100
(main) place of residence?					
(main) place of work / training					

End of the block: Mobility: Availability

Beginning of the block: Mobility: Commute

Which means of transport do you normally use (i.e. before / after the COVID-19 pandemic) to get from your (main) place of residence to your (main) place of work / training? (Please tick all that apply)

- ◯ Walk
- ◯ Bike
- ◯ E-Bike
- ◯ E-Scooter
- ◯ Car
- ◯ Motorbike / scooter
- ◯ Public transport
- ◯ Other ________________________________

Do you usually commute alone?

- ◯ Yes
- ◯ No

Do you have a parking space at your place of work / training?

- ◯ Yes
- ◯ No

End of the block: Mobility: Commute

Beginning of the block: Mobility: Means of transport

How often do you currently use the following modes of transport?

	(almost) daily	several times each week	several times each month	less often / never
Car	○	○	○	○
Public transport	○	○	○	○
Uber / Taxi	○	○	○	○
Motorbike / scooter	○	○	○	○
Bike	○	○	○	○
E-Bike	○	○	○	○
E-Scooter	○	○	○	○

Do you plan to change the frequency of transport use in the next 3 months?

○ Yes

○ No

What do you plan to do?

	use less often	no change	use more often
Car	○	○	○
Public transport	○	○	○
Uber / Taxi	○	○	○
Motorbike / scooter	○	○	○
Bike	○	○	○
E-Bike	○	○	○
E-Scooter	○	○	○

End of the block: Mobility: Means of transport

Beginning of the block: Mobility: Public transport

Do you currently have one or more public transport subscriptions? (Please tick all that apply)

○ GA (first class)

○ GA (second class)

○ Halbtax

○ Verbund (e.g., ZVV Netzpass, U-Abo, Libero-Abo, Tarifverbund Nord-Westschweiz (TNW))

○ Strecken Abonnement

○ Mehrfahrtenkarte

○ Seven 25

○ Other ____

Is one or several of your subscriptions paid by your employer or otherwise at least partially externally financed?

○ Yes

○ No

Do you plan to make any changes to your public transport subscriptions in the next 3 months?

○ Yes

○ No

What do you plan to do?

	cancel / not extend	no change	buy (another)
GA (first class)	○	○	○
GA (second class)	○	○	○
Halbtax	○	○	○
Verbund	○	○	○
Strecken Abonnement	○	○	○
Mehrfahrtenkarte	○	○	○
Seven 25	○	○	○
Other	○	○	○

End of the block: Mobility: Public transport

Beginning of the block: Mobility: E-Scooter

The following questions relate to your last ride on an e-scooter.

When was your last ride on an e-scooter?

○ In the past 7 days.

○ My last ride was more than 7 days ago.

○ I have never ridden an e-scooter.

At what time of day did you take this trip?

- ○ During the week: in the morning
- ○ During the week: at noon
- ○ During the week: in the evening
- ○ During the week: at night
- ○ On the weekend: in the morning
- ○ On the weekend: at noon
- ○ On the weekend: in the evening
- ○ On the weekend: at night

How long did this ride last?

- ○ less than 5 min
- ○ 5 to 10 min
- ○ 10 to 15 min
- ○ more than 15 min

Did you rent the e-scooter for the ride (e.g., from Bird / Lime / Voi / Tier) or do you own it yourself?

- ○ Rented
- ○ Own

What was the destination of this ride?

○ Work or training

○ Restaurant / bar

○ Public transport stop

○ Home

○ Leasure activity

○ Shopping / errands

○ Family and friends

○ Other ____

Why did you choose an e-scooter as your means of transport? (Multiple answers possible)

○ It is fast.

○ It is fun.

○ It is cheap.

○ To try it.

○ Other ______________________________________

Would you have taken the trip if the e-scooter had not been available?

○ Yes

○ No

Which alternative mode of transport would you have chosen?

- ◯ Walk
- ◯ Bike
- ◯ E-Bike
- ◯ Car
- ◯ Public transport
- ◯ Carsharing
- ◯ Uber
- ◯ Taxi
- ◯ Motorbike / scooter

End of the block: Mobility: E-Scooter

Beginning of the block: Travel priorities

What are your general priorities when traveling?

	Unimportant	Rather unimportant	Rather important	Important	No answer
Price	◯	◯	◯	◯	◯
Flexibility	◯	◯	◯	◯	◯
Comfort	◯	◯	◯	◯	◯
Time	◯	◯	◯	◯	◯
Environ-ment	◯	◯	◯	◯	◯

End of the block: Travel priorities

Thank you for filling out this first questionnaire. We will send you information on the second part of the study, the mobility diary, via email.