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E-biking in Switzerland (EBIS)

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Zusammenfassung

Elektrische Fahrräder verändern die urbane Mobilität grundlegend. Das Projekt E-Biking in der Schweiz (EBIS) hat zum Ziel, besser zu verstehen, wie E-Bikes genutzt werden, wer sie verwendet, wie sie das Mobilitätsverhalten beeinflussen und welche Rolle sie bei der Reduktion von CO_2-Emissionen spielen können. Durch die Erhebung und Analyse von Daten von fast 4'000 Teilnehmenden aus der ganzen Schweiz mittels GPS-Tracking und Umfragen liefert die Studie detaillierte und umsetzbare Erkenntnisse über das Potenzial des E-Bikings als nachhaltige Mobilitätsform.

Über 2.8 Millionen Wegabschnitte wurden über mehrere Wochen hinweg aufgezeichnet. Die Daten geben Aufschluss über Routenwahl, Fahrtdauer und saisonale Muster von E-biking und Velofahren. Eine tracking-App erfasste die gewählten Verkehrsmittel automatisch, und die Teilnehmenden wurden gebeten, diese zu validieren und gegebenfalls zu korrigieren. Ausserdem beantworteten sie Umfragen bezüglich Substitution von Verkehrsmitteln und ihren Präferenzen für Fahrradinfrastruktur. Wir konnten aufgrund von zusätzlichem Funding und gezielter Rekrutierung die urbanen Agglomerationen Aarau, Basel und Zürich überproportional berücksichtigen. Dies erlaubt es uns, regionenspezifische Resultate zu generieren. Die im Rahmen dieser Studie erhobenen Daten zum beobachteten täglichen Veloverhalten werden der wissenschaftlichen Gemeinschaft zur Verfügung gestellt und leisten damit einen Beitrag zu Open Science.

Durch die Schätzung von Routenwahlmodellen identifizieren wir die relative Bedeutung verschiedener Eigenschaften der Velo-Umgebung. Die Modelle basieren sowohl auf beobachteten Präferenzen (tatsächliche Fahrten, aufgezeichnet über die App) als auch auf erklärten Präferenzen (Umfragedaten). Zentrale Faktoren für die Routenwahl sind die Verkehrsmenge, Höhenunterschiede, die Qualität des Velowegs sowie die physische Trennung zwischen Velos motorisiertem Verkehr. Die Präferenzen variieren nach Geschlecht und Fahrhäufigkeit. Es zeigt sich eine breite Unterstützung für bessere Veloinfrastruktur, sowohl auf Haupt- als auch auf Nebenstrassen.

EBIS beinhaltet eine randomisierte Kontrollstudie. In diesem Experiment wurde die Hälfte der Teilnehmenden mit einem Mobilitätspreis konfrontiert, der sich an den wichtigsten externen Kosten des Verkehrs orientiert. Um dies in einer freiwilligen Stichprobe umzusetzen, erhielten die Teilnehmenden der Interventionsgruppe ein Budget, von dem danach die Zahlungen abgezogen wurden; der Rest des Budgets konnten die Teilnehmenden behalten. Der kausale Effekt der Intervention ergibt sich durch den Vergleich der Verkehrsentscheidungen der Interventionsgruppe mit jener der Kontrollgruppe. Die Bepreisung reduziert den Autoanteil signifikant und erhöht im Gegenzug die Nutzung von E-Bikes sowie des öffentlichen Verkehrs. Die totale Reisedistanz über alle Verkehrsmittel bleibt unverändert. Der Effekt wird insbesondere getrieben durch

Besitzerinnen und Besitzer von S-Pedelecs (E-Bikes mit elektrischer Unterstützung bis 45 km/h).

Die Studie schliesst mit einer Analyse der momentanen CO_2-Reduktionen durch E-Biking sowie des Einsparpotenzial unter verschiedenen Szenarien der zukünftigen Verbreitung von E-Bikes. Die CO_2-Einsparungen hängen direkt vom jeweils ersetzten Verkehrsmittel ab. Über eine retrospektive Umfrage erhoben wir Informationen zum Substitutionsverhalten und berechnen die daraus resultierenden CO_2-Einsparungen anhand verkehrsmittelspezifischer Emissionsfaktoren. Mithilfe von Daten aus dem Mikrozensus Mobilität und Verkehr skalieren wir unsere Ergebnisse auf die nationale Ebene. Basierend auf dem beobachteten Substitutionsmuster berechnen wir eine Reduktion der CO_2-Emissionen bei E-Bike-Fahrten um 78%. Dies entspricht einer gesamthaften Reduktion von 22,000 tCO_2 pro Jahr, oder 0.2% der Transportemissionen. Szenarien mit einer stärkeren Verbreitung von E-Bikes zeigen ein erhebliches Potenzial zur Senkung der verkehrsbedingten Emissionen in der Schweiz.

E-Bikes leisten bereits heute einen Beitrag zur Emissionsreduktion. Mit politischen Fördermassnahmen könnte ihre Wirkung deutlich gesteigert werden. Um das volle Potenzial der Klimareduktion durch E-Biking auszuschöpfen müssen auch Bevölkerungsgruppen erreicht werden, die das E-Bike bisher nicht als realistische Alternative zum Auto oder zum öffentlichen Verkehr betrachten. Unsere Ergebnisse implizieren, dass der Ausbau und die Verbesserung der Veloinfrastruktur – insbesondere physisch getrennte Routen – das E-Biking attraktiver machen können. In Kombination mit einer Verkehrs-Bepreisung, welche die externen Kosten internalisiert, könnte dies den Umstieg auf nachhaltige Verkehrsmittel deutlich beschleunigen.

EBIS generiert einen weltweit einmaligen Datensatz zur E-Bike-Nutzung. Die Studie zeigt, dass E-Bikes mehr als nur ein Trend sind, sondern ein wirkungsvolles Instrument für eine nachhaltige und gesunde urbane Mobilität. Indem sie aufzeigt, wer E-Bikes nutzt, wie sie eingesetzt werden und welche politischen Massnahmen ihre Wirkung verstärken können, bildet diese Studie eine fundierte Grundlage für eine evidenzbasierte Verkehrs- und Klimapolitik in der Schweiz.

Summary

Electric bicycles are transforming urban mobility. The EBIS (E-Biking in Switzerland) project set out to better understand how E-bikes are used, who uses them, how they impact travel behavior, and what role they can play in reducing carbon emissions. By collecting and analyzing data from nearly 4,000 participants from across Switzerland through GPS tracking and surveys, the study provides detailed and actionable insights into the potential of E-biking as a sustainable mode of transport. Over 2.8 million stages were recorded over several weeks, providing information on route choice, duration and seasonal patterns of E-biking and cycling, as well as on transport mode choice more generally. A tracking app automatically detects the used mode, and the participants were asked to validate or correct it. They also completed surveys on mode substitution and preferences for cycling infrastructure. Thanks to additional funding and targeted outreach, we were able to over-sample the metropolitan regions of Aarau, Basel and Zurich. This allows us to generate region-specific results. The data on real-world cycling behavior gathered in the course of this study will be shared with the scientific community and thus contribute to open science.

By estimating route choice models we identify the relative importance of different attributes of the cycling environment. The models are based on both revealed preference (real trips recorded through the app) and stated preference (survey) data. Key factors for route choice include traffic exposure, elevation gain, the quality of the bicycle infrastructure, and whether cyclists are physically separated from cars. Preferences varied by region, gender and cycling frequency, with strong support for better infrastructure on both main and side streets.

An important part of the study consisted of a randomized control trial. In this experiment, we exposed some of the participant to transport pricing based on the main external costs of transport. To do this in a voluntary sample, we provided the participants in the treatment group with a budget from which the payments were then subtracted; the remaining balance was to be kept by the participants. The treatment effect is computed by comparing the transport choices of the treated group with that of the control group. We find that the pricing significantly reduces car use and shifts travel towards E-biking and public transport, whereas overall travel distances remain unchanged. The effect is mainly driven by owners of S-pedelecs (E-bikes with an electric support of up to 45 km/h).

The study concludes with an analysis of the current reductions in carbon emission due to E-biking, and the potential carbon savings under different scenarios of E-bike expansion. The carbon savings depend directly on the mode that is substituted by the E-bike. We elicit information about mode substitution from the study participants using a “retrospective” survey, and compute the resulting carbon savings with mode-specific

emission factors. Using data from the Swiss Mobility and Transport Microcensus, we scale our results to the national level. Based on the observed substitution pattern, we estimate a reduction in carbon emissions for E-bike trips of 78%, which translates into 22'000 tons of CO_2 saved annually, reducing emissions of all land-based transport in Switzerland by 0.2%. Scenarios assuming wider E-bike adoption point to notable potential for an increased role of E-biking in lowering transport-related emissions in Switzerland.

E-bikes are already contributing to emission reductions. With supportive policies, their role could be greatly expanded. Integrating E-bikes into climate action plans could therefore yield substantial gains. To realize the full potential of E-biking, efforts must reach broader demographics that currently do not consider the E-bike to be a viable alternative to driving or public transport. Our results imply that expanding and improving cycling infrastructure–especially routes with physical separation from cars –can make E-biking more attractive. Combining such measures with transport pricing that internalizes the main (as of yet) unpriced external costs of transport would significantly accelerate the shift towards more sustainable modes of transport.

EBIS delivers one of the most comprehensive datasets on E-bike use to date. It confirms that E-bikes are more than a trend—they are a powerful lever for sustainable, healthy, and low-carbon urban mobility. By showing who uses E-bikes, how they are used, and what kinds of policies can enhance their impact, this study provides a strong foundation for evidence-based transport and climate policy in Switzerland.

Résumé

Les vélos électriques transforment la mobilité urbaine. Le projet EBIS (E-Biking in Switzerland) vise à mieux comprendre comment les vélos électriques sont utilisés, qui les utilise, comment ils influencent les comportements de déplacement et quel rôle ils peuvent jouer dans la réduction des émissions de carbone. En collectant et en analysant des données de près de 4 000 participants dans toute la Suisse via un suivi GPS et des enquêtes, l'étude fournit des informations détaillées et exploitables sur le potentiel du vélo électrique en tant que mode de transport durable.

Plus de 2,8 millions de trajets ont été enregistrés sur plusieurs semaines, fournissant des informations sur le choix d'itinéraire, la durée et les variations saisonnières de l'usage du vélo électrique et du vélo classique, ainsi que sur le choix du mode de transport de manière plus générale. L'application de suivi détecte automatiquement le mode de transport utilisé, et les participants étaient invités à le valider ou à le modifier. Ils ont également rempli des enquêtes sur la substitution des modes de transport et leurs préférences en matière d'infrastructures cyclables. Grâce à un financement supplémentaire et à une sensibilisation ciblée, nous avons pu suréchantillonner les régions métropolitaines d'Aarau, Bâle et Zurich. Cela nous permet de générer des résultats spécifiques à chaque région. Les données sur le comportement cycliste réel recueillies au cours de cette étude seront partagées avec la communauté scientifique et contribueront ainsi à l'*open science* .

En estimant des modèles de choix d'itinéraire, nous identifions l'importance relative des différents attributs de l'environnement cyclable. Les modèles sont basés à la fois sur des préférences révélées (trajets réels enregistrés via l'application) et sur des préférences déclarées (enquêtes). Les principaux facteurs influençant le choix d'itinéraire incluent l'exposition au trafic, le dénivelé, la qualité des infrastructures cyclables, et la distance de séparation physique entre les cyclistes et les voitures. Les préférences varient selon la région, le genre et la fréquence de pratique, avec un fort soutien en faveur de meilleures infrastructures sur les axes principaux comme secondaires.

Une partie importante de l'étude consistait en une expérience contrôlée randomisée. Dans cette expérience, certains participants ont été exposés à une tarification des transports basée sur les principaux coûts externes. Pour réaliser cela dans un échantillon volontaire, nous avons fourni aux participants du groupe de traitement un budget à partir duquel les paiements ont été déduits ; le solde restant leur revenait. L'effet du traitement est mesuré en comparant les choix de transport du groupe traité à ceux du groupe témoin. Nous constatons que la tarification réduit significativement l'usage de la voiture et oriente les déplacements vers le vélo électrique et les transports publics, tandis que les distances de déplacement totales restent inchangées.

L'effet est principalement porté par les propriétaires de S-pedelecs (vélos électriques avec assistance jusqu'à 45 km/h).

L'étude se termine par une analyse des réductions actuelles d'émissions de carbone dues au vélo électrique et du potentiel de réduction dans différents scénarios d'expansion. Les économies de carbone dépendent directement du mode de transport substitué par le vélo électrique. Nous avons recueilli des informations sur cette substitution via une enquête « rétrospective », et avons calculé les économies de carbone à l'aide de facteurs d'émission spécifiques à chaque mode. En utilisant les données du Microrecensement Mobilité et Transports suisse, nous avons extrapolé nos résultats au niveau national. En se basant sur le schéma de substitution observé, nous estimons une réduction des émissions de carbone des trajets en vélo électrique de 78 %, ce qui équivaut à 22'000 tonnes de CO_2 économisées annuellement, soit une réduction de 0,2 % des émissions du transport terrestre en Suisse. Des scénarios d'adoption plus large du vélo électrique indiquent un fort potentiel de réduction supplémentaire des émissions liées au transport.

Les vélos électriques contribuent déjà à la réduction des émissions. Avec des politiques de soutien appropriées, leur rôle pourrait être considérablement renforcé. Intégrer les vélos électriques dans les plans d'action climatique pourrait ainsi produire des bénéfices significatifs. Pour exploiter pleinement leur potentiel, les efforts doivent toucher des groupes démographiques plus larges qui ne considèrent pas encore le vélo électrique comme une alternative viable à la voiture ou aux transports publics. Nos résultats indiquent que le développement et l'amélioration des infrastructures cyclables – notamment des voies séparées physiquement des voitures – peuvent rendre le vélo électrique plus attractif. La combinaison de telles mesures avec une tarification des transports internalisant les principaux coûts externes (encore non tarifés) accélérerait considérablement le basculement vers des modes de transport plus durables.

L'étude EBIS fournit l'un des ensembles de données les plus complets à ce jour sur l'utilisation des vélos électriques. Elle confirme que les vélos électriques ne sont pas qu'une tendance – ils sont un levier puissant pour une mobilité urbaine durable, saine et à faible émission de carbone. En montrant qui utilise les vélos électriques, comment ils sont utilisés, et quelles politiques peuvent en renforcer l'impact, cette étude offre une base solide pour une politique des transports et du climat fondée sur des données probantes en Suisse.

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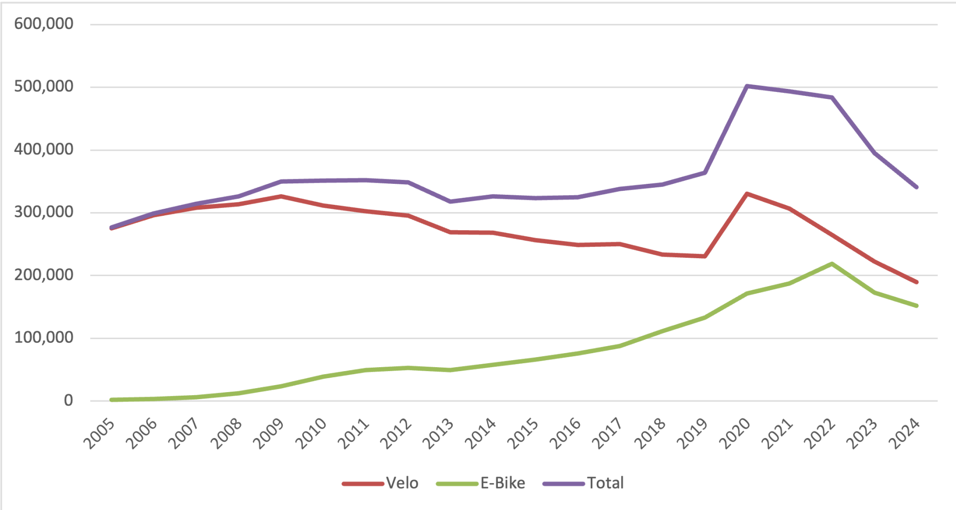
1 Introduction

Electric-assist bicycles are in great demand, overcoming some key limitations of conventional bicycles. E-bikes make cycling an attractive option for a larger segment of the population. Figure 1.1 shows sales trends. With sales rates around 20% over many years until the COVID pandemic, E-biking may be the most dramatic change currently occurring in urban mobility.

Figure 1.1: E-bike and Bicycle Sales in Switzerland (2005-2024)



Source: https://www.velosuisse.ch/wp-content/uploads/2025/03/Gesamtstatistik2005-2024.pdf

Switzerland distinguishes between two categories of E-bikes. Standard E-bikes (or pedelecs) support the rider until 25 km/h and with a maximum power of 500 W. They are classified as mopeds, allowed on cycle lanes and require no license or registration. On the other hand, fast E-bikes or S-pedelecs (S for speed) support riders until 45 km/h with up to 1000 W. These are also classified as mopeds but require a license plate, insurance, and helmet (Swiss Federal Roads Office, 2020). Throughout this report, we refer to E-bikes when we mean to include both types, and to "standard E-bikes" and "S-pedelecs" when we refer to the slower and the faster option, respectively.

The potential for cycling to reduce carbon emissions in the transport sector is gaining prominence among local governments, as more and more cities are implementing ambitious climate goals. However, the extent to which E-bikes can (and do) contribute to a more energy efficient and sustainable transport system in Switzerland is insufficiently understood. A more profound understanding of cyclists' choices and an accurate quantification of energy consumption and carbon emissions is a prerequisite to properly value the role and potential of E-biking in a future, sustainable Swiss transport system. Our project investigates the behavior of cyclists in Switzerland, including their preferences for route attributes, mode-specific determinants, valuation of time and the substitution between E-bikes and other modes. It also estimates the likely scope of carbon and energy savings (hereafter referred to as carbon savings) in the transport sector as a result of E-biking. It thus provides an evidence-based foundation for decision-making in transport policy.

For this project, we recruited close to 4'000 persons in Switzerland and recorded their transport behavior with a GPS-based tracking app for several weeks. We also carried out several surveys with this sample. The resulting data is analyzed in qualitatively different ways in four work packages (WPs).

The first WP (section 3) describes the gathered data, including distances by mode, trip purposes and socio-demographic characteristics of the sample. It thus provides a general understanding of who uses E-bikes, for what kind of trips, and for what purposes. It also describes the sampling and measurement methodology, attrition rates etc. and thus serves as a “data basis" for the rest of the project.

We use our highly disaggregated panel data to model and infer cyclists' preferences by estimating route choice models (section 4). In addition to this "revealed preference" (RP) approach, we also engage in a stated preference (SP) analysis of how cyclists choose between different routes, based on a survey. Among the examined determinants are the bicycle infrastructure (such as separated bicycle paths or on-street bicycle lanes), traffic volume, topographical characteristics as well as attributes of the riders themselves, such as gender.

The remaining two WPs of our project focus on the substitution between E-bikes and other modes, and the resulting implications for emissions and other external costs of transport. In section 5, we present the results of a randomized controlled trial involving a subset of our panel. In this field experiment, we simulate the effects of future transport policies by introducing a full-cost mobility pricing intervention for the treatment group. We find that pricing in the external costs of driving and public transport leads to a statistically significant substitution away from the car towards the E-bike and public transport.

In section 6, we estimate the extent to which E-biking has already reduced CO_2-emissions in our sample and in Switzerland, and the scope for future reductions in different scenarios of E-bike expansion. The most important determinant for E-bike related carbon savings is mode substitution. To learn about this, we rely on a survey in which we ask E-bikers to identify the mode of transport they would have chosen had they not owned an E-bike at the time of travel. By linking these results with emission rates by mode, we can compute the reduction in CO_2 emissions due to E-biking. We also apply our model to the Swiss Microcencus of Transport to compute realized and potential emissions savings due to E-biking in the general population.

2 Related literature

Prior to the advent of reliable GPS-tracking devices, self-reported travel diaries such as the Mobidrive study formed the basis for research on transportation behavior (Chalasani and Axhausen, 2004). Travel diaries are still common today; the Swiss Mobility and Transport Microcensus (MTMC) uses self-reported one-day travel diary data (BFS, 2023). However, GPS-tracking data is increasingly common and has many advantages over self-reported travel diaries (Greene et al., 2016; Molloy et al., 2023). Passive GPS tracking through smartphone apps allows for collection over days or weeks to better reflect day-to-day variation, rather than the one-day standard used in many travel diaries including the MTMC (Greene et al., 2016). GPS tracking also picks up trips which go under-reported in conventional travel diaries due to memory and response burden (Janzen et al., 2018; Stopher et al., 2007) and captures spatial information on route choice (Marra et al., 2019).

GPS-tracking studies to study cyclists have recently proliferated (Scott et al., 2021; Ton et al., 2017; Casello and Usyukov, 2014; Meister et al., 2023; Dane et al., 2019; Plazier et al., 2017; Menghini et al., 2010). The Mobility in Switzerland (MOBIS) project, which was an RCT study investigating the effects of transport pricing on travel behavior using GPS tracking (Axhausen et al., 2021; Molloy et al., 2023), included GPS data from over 4’000 cycling trajectories, over 800 of which are from E-bikes. The EBIS study builds upon the methodology from the MOBIS study, but whereas MOBIS recruited participants from the general Swiss population, EBIS specifically focused on cyclists and E-bikers to create a unique, cycling-specific dataset (see for 3.1.1).

There is also a growing body of literature focusing on mode-shift potential towards E-bikes (Rayaprolu et al., 2020; Bigazzi and Wong, 2020; Moser et al., 2018). Several studies have exhibited a shift away from car-driving after the acquisition of an E-bike (Sun et al., 2020; Kroesen, 2017; Andersson et al., 2021). Bigazzi and Wong (2020) conducted a global literature review and showed that E-bikes mostly substitute trips by public transport, conventional bicycle and car, depending on the mode-share in the country of the study. All studies used in their literature review evaluated mode substitution by simply asking E-bikers how their travel behavior would have been different if they had no E-bike available, rather than using revealed preference data. The generation of new travel due to E-bikes was not addressed by the majority of the studies in their literature review. Trip generation is an important aspect of travel behavior and something that EBIS surveys attempt to account for. Moser et al. (2018) studied the long-term effects on driving rates of a free, two-week E-bike trial and found decreased habitual car use even one full year after the trial. Reck et al. (2022) used GPS data from 500 travellers in a discrete choice model to estimate mode replacement as a result of shared micro-mobility. A few studies have estimated carbon emission savings resulting from mode-shift towards E-biking (Philips et al., 2020; McQueen et al., 2020; Bucher et al., 2019). The large scale of the EBIS dataset enriches the available data for future research on mode-choice towards bike and E-bike.

From an economic point of view, price-based instruments that accurately capture the external costs of transportation are an efficient way to internalize externalities. Several studies have examined fuel taxes as a means to incorporate externalities associated with transportation (Santos, 2017; CE Delft, 2019b). However, these studies generally fail to adequately consider the complete range of external costs related to transportation (Parry et al., 2007).

A number of studies have looked at optimal congestion pricing, which is also an efficient means of regulation, as for example drivers with a high value of time travel at the peak of rush hour, reducing those trips that people regard as least important (Vickrey, 1969; Arnott et al., 1993; Hall, 2018; Eliasson, 2021). Urban road congestion pricing has already been successfully introduced in a number of cities (Eliasson, 2021). Evidence from quasi-experimental studies conducted in London, Milan, and Bergen (Norway) indicates that the implementation of congestion charges was successful in reducing both traffic congestion and air pollution levels (for London, 2007; Gibson and Carnovale, 2015; Isaksen and Johansen, 2021). Evidence from the congestion pricing system in Stockholm highlights resulting departure time shifts to off-peak times, and a shift towards public transit (Karlström and Franklin, 2009). Yang et al. (2020) ascertain the implications of an ideal road congestion charge in Beijing. Their findings indicate a positive impact on overall social welfare and a noteworthy increase in travel speeds during peak hours (by 11%). However, these charges often remain constant and are unable to adequately accommodate the fluctuating nature of traffic congestion, thus not reflecting the full external costs of transport (Hintermann et al., 2025). Additionally, these strategies predominantly focus on a single mode of transportation.

Previous field experiments with monetary incentives include the following: Martin and Thornton (2017) implement a large road use pricing experiment that installed GPS responders in 1'400 vehicles using different charging types. They find that constant charges primarily lead to reductions in high-speed driving and off-peak road use, whereas charges targeted at peak times or central areas proved to be more successful in relieving congestion. Ben-Elia and Ettema (2011) conducted a field experiment in the Netherlands to investigate the impacts of different kinds of rewards on commuter behavior using in-vehicle tracking. The study reveals that financial incentives serve as an effective means to decrease rush-hour driving, encourage a shift towards off-peak times, and increase the utilization of public transit, cycling, and remote work. Tsirimpa et al. (2019) find that incentivizing participants towards sustainable multimodal choices using a smartphone app increases the use of public transport and walking.

We are aware of several other RCTs in the transportation sector that incorporate financial incentives. Rosenfield et al. (2020) conduct an RCT with both an informational campaign and monetary incentives involving 2'000 employees at the Massachusetts Institute of Technology aimed at reducing parking demand. In neither of the three treatment arms do they find a significant reduction in car usage, nor an increase in use of alternative modes. Hintermann et al. (2025) implement Pigovian transport pricing in a large-scale field experiment using the tracking app "Catch my Day". They find a significant reduction in the external costs of transport due to the pricing treatment, being a consequence of mode substitution and a shift of departure times. Kreindler (2024) conducts a field experiment to examine the effect of peak-hour traffic congestion pricing using a smartphone app. The commuter responses in the experiment reveal moderate schedule inflexibility and a high value of time, suggesting limited commuter welfare benefits from peak-spreading traffic policies in cities like Bangalore.

The RCT included in this project contributes to the literature of transport economics in various ways. Following Hintermann et al. (2025), we implement an extensive marginal cost pricing scheme varying across time and space, allowing for an in-depth analysis of the response of E-bikers to such a policy. This provides a useful benchmark for policymakers concerning simplified versions of transport pricing and making efforts towards the decarbonization of the transport sector.

The employed study design, where participants must pay from a mobility budget based on their true travel behavior, is the closest one can get to testing the effect of mobility pricing without implementing it in practice. It is the first large-scale E-bike pricing experiment regarding externalities, estimating causal effects to be expected from a potential future implementation of mobility pricing.

The retrospective survey is suitable to estimate substitution patterns of the E-bike. The mode of transport that gets substituted by whom is not clear so far as seen for example in the Netherlands from the national mobility survey (de Haas et al., 2021; Kroesen, 2017; Lee et al., 2015; Plazier et al., 2017). However, the findings point in the direction of a decline of traditional bikes due to the usage of E-bikes (Kroesen, 2017; Lee et al., 2015). In general, these surveys are able to provide helpful insights into motivation and substitution effects. But this stated preference data is often prone to bias of the participants (Ben-Akiva et al., 1994; Morikawa, 1989). Furthermore, often only a snapshot of one-day travel behavior is used to calculate substitution effects, which might not be representative of repeated travel behavior. Revealed preference data has the advantage that it tracks real travel behavior and is, therefore, less prone to recall or social desirability bias (Morikawa, 1989). GPS-tracking is a valuable tool to gather large datasets on travel behavior to predict mode substitution (Bigazzi and Wong, 2020; Reck et al., 2022). For example, Reck et al. (2022) used a MMNL with a focus on shared micro-mobility modes such as e-scooters as well as E-bikes to predict substitution modes in Switzerland. They showed that the substitution of a certain mode is dependent on the distance traveled. The shorter the distance, the more walking-km are substituted by personal and shared E-bikes, while for longer trips, car and PT are more often replaced (Reck et al., 2022).

As the E-bike can have an impact on modal shift there is a vast literature on the E-bikes' impact on externalities in the transport sector, especially CO_2 emissions (Astegiano et al., 2019; Bucher et al., 2019; Goodman et al., 2019; Fukushige et al., 2023; McQueen et al., 2020; Philips et al., 2020, 2022; Piatkowski et al., 2015; Raposo and Silva, 2022; Winslott-Hiselius and Svensson, 2017). Different approaches were used to induce these emission savings, such as GPS from shared E-bike systems (Fukushige et al., 2023; Raposo and Silva, 2022), scenario analysis (Astegiano et al., 2019; Bucher et al., 2019) or surveys (McQueen et al., 2020; Winslott-Hiselius and Svensson, 2017). In Switzerland, Bucher et al. (2019) predicted the greenhouse gas emission reductions in Switzerland due to the E-bike. Their prediction is rooted in energy demand connected to different weather scenarios. They estimate a reduction of up to 17.5% of the fossil fuel-based emissions of commuting-related trips due to the E-bike.

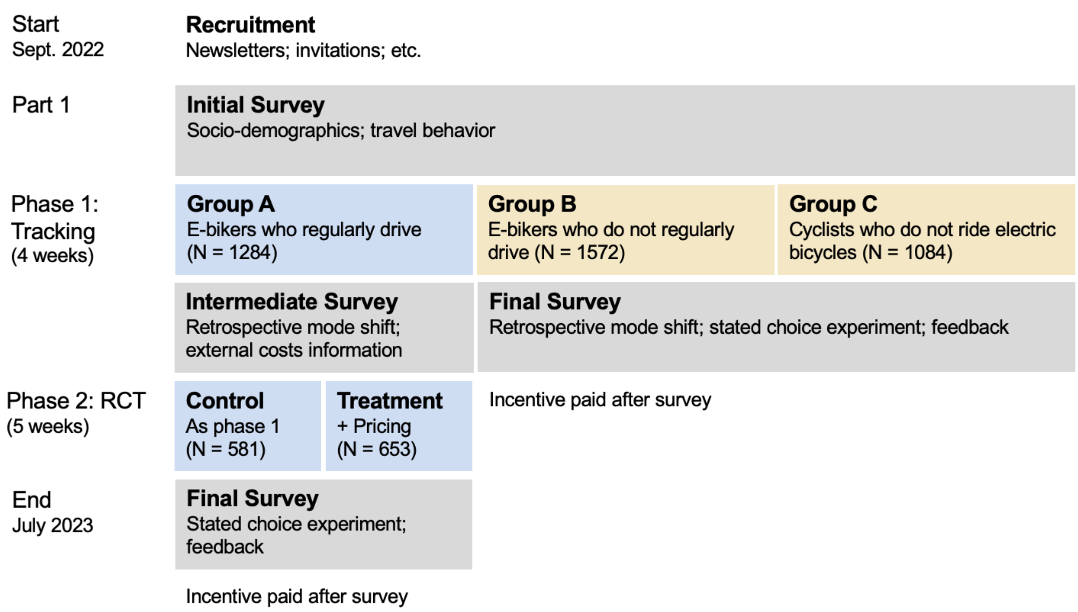
3 Tracking panel and data description

3.1 Study design

In this section, we describe the design of the study, the tracking panel, and the data is the basis for all sections. We also provide summary statistics about E-biking and cycling in Switzerland. This section is based on Heinonen et al. (2024).

The EBIS study design began with comprehensive recruitment of E-bikers and cyclists. The study then consisted of a series of surveys accompanied by GPS-tracking of travel behavior. The initial survey assessed basic socio-demographic and mobility-related variables, which allowed us to group participants into three groups: E-bikers who frequently use a car (group A), E-bikers who do not frequently use a car (group B), and bicyclists who do not ride electric bikes (group C). The study period differed by group. Participants in group A were part of the RCT. Their study period was nine weeks: a four week tracking phase (Phase 1) followed by a five week RCT phase (Phase 2). Groups B and C did not qualify for the RCT and only completed Phase 1, the four-week tracking period. The goals and structure of each study phase are explained in further detail below.

Figure 3.1: Overview of EBIS study design



Note: Group A participants who dropped out before the intermediate survey were not assigned a treatment group.

3.1.1 Recruitment

The recruitment strategy for EBIS specifically targeted E-bikers and cyclists across the German- and French-speaking regions of Switzerland. This was necessary because it is cost prohibitive to recruit enough E-bikers through representative sampling of Swiss households due to the relatively low prevalence of E-biking. This precludes us from assessing the prevalence of E-biking in Switzerland, but nevertheless allows for ample insights about E-bikers' and cyclists' travel behavior. The recruitment efforts also over-sampled the cantons of Aargau, Zurich, Basel-Land and Basel-Stadt because these cantons provided additional funding for the study. Several recruitment channels were employed and are described below, in chronological order. Their success rates, including numbers of people contacted and consequently retained for the study, are presented in section 3.3.

- **Personal email:** The recruitment process started in September 2022 with email invitations sent to cyclists on the email list of Pro Velo, an organization promoting the interests of cyclists in Switzerland. These individuals agreed to be contacted for this study in a prior, unrelated survey. Email addresses were also gathered by the research team at a bicycle themed week in the city of Zurich (Zurich Cycle Week).

- **Social media:** A social media campaign launched in September 2022 on Instagram and Facebook targeting 18-65 year-old individuals in the cantons of Basel-Stadt, Basel-Land, Aargau and Zurich with an interest in E-bikes. The city of Zurich and the canton of Aargau also posted an advertisement for the study on their social media accounts in November 2022.

- **Letter from canton:** In Switzerland, s-pedelecs must be registered with the Department of Motor Vehicles (DMV) and use a license plate. This enabled cooperation with the DMV in cantons Basel-Stadt (September 2022), Aargau (October 2022) and Zurich (March 2023). In these cantons, the DMV agreed to send invitation letters to registered s-pedelec owners. Representing over 10'000 letters sent in Zurich, this was the primary recruitment channel utilized in 2023.

- **Newsletter:** In October 2022, the study was highlighted in the newsletters of Veloplus, a large Swiss bike retailer, and Verkehrs-Club Schweiz, an association which provides mobility-related insurance and engages in cycling-friendly politics. Additionally, miloo and Stromer, two Swiss bike manufacturers, promoted the study to their customer base in March and April 2023.

- **Link panel:** From October to December 2022, the research institute Link contacted individuals in the French- and German-speaking parts of Switzerland who own an E-bike and a car. Individuals from this recruitment channel received a reward of one Swiss franc from Link for completing the introductory survey. Continuation in the study was rewarded identically to the other channels (see Sections 3.1.2 and 3.1.3 for further information on study incentives).

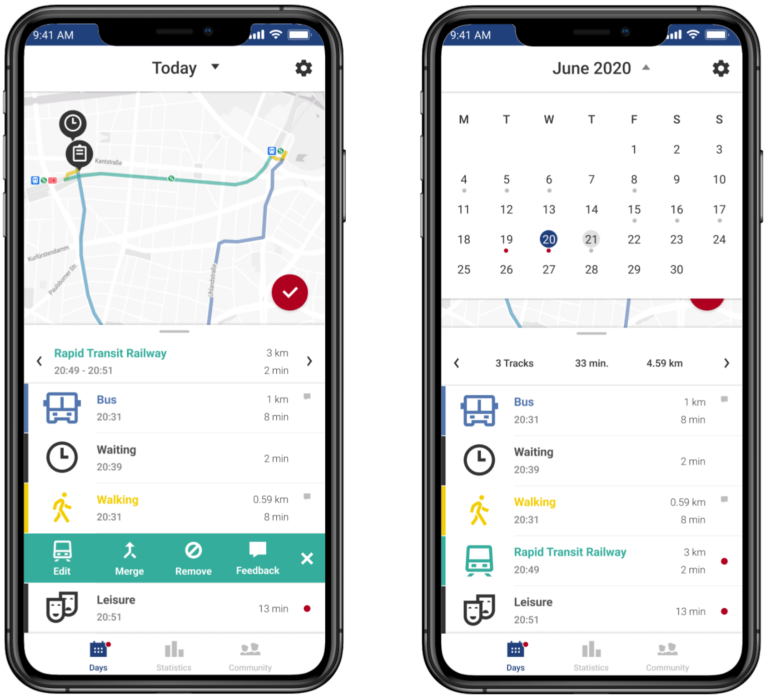
- **Flyer:** From October to December 2022, flyers were attached to E-bikes and handed out to cyclists in Zurich and Basel.
- **Intranet ad:** In November 2022, ads were placed on the intranet landing pages of cantonal administrations and university project teams in Basel. Similarly, the cantonal administration of the canton of Aargau placed ads in its intranet in April 2023.

Recruited participants filled out the introductory online survey, where potential participants were asked about their mobility behavior, their vehicle, bike and E-bike ownership, and about socio-demographics including age, income, nationality, height and weight. The initial survey had a response burden of 150 on the response burden scale developed by Schmid and Axhausen (2019). This corresponds to an approximate completion time of 10-15 minutes. Participants qualified for the tracking study if they were at least 14 years old, lived in Switzerland, owned or regularly rode a bike, used a smartphone, could walk 200 meters without support, and agreed to be tracked. People who owned a bike qualified for the study even if they did not regularly ride it because their tracking data was deemed of interest for estimating mode choice models that contain bike within the choice set.

3.1.2 Tracking

The tracking was conducted using the Catch-my-Day app by MotionTag. Figure 3.2 shows two screenshots of the tracking app. Once initialized, the app automatically identifies GPS tracks and their respective modes of travel. The automated mode detection includes car, bus, train, tram, subway, walking, and cycling. Participants are retroactively able to view, validate, or correct the travel modes, including to modes that are not detected automatically. Molloy et al. (2023) found that MotionTag's mode detection algorithm works well, with 92% overall accuracy. Some modes, including walking, car, and tram, performed even better. 79% of bicycle trips were correctly identified, with the biggest confusion being with walking. To account for potential mode misdetection users were encouraged to validate their activities and trips. 92% of trips overall were validated. The main limitation of the MotionTag's algorithm is that it cannot reliably differentiate between E-bikes and regular bikes. Therefore, when not specifically validated otherwise by the user, detected "bicycle" trips were imputed as either bicycle or E-bike based on the user's bike ownership reported in the survey.

Figure 3.2: The “Catch my Day” interface



Note: GPS tracking app on iPhone (left: map view, right: calendar view).

After activating their account within the app, users received automated emails which were sent out by monitoring scripts. The emails included tips for using the app, links to additional materials and documentation, weekly travel reports (shown in the dashed section in the top-left of Figure 3.3), and links to the intermediate and final questionnaires (see section 3.1.4). The monitoring script also detected whether participants' GPS-tracking was working properly and whether participants were validating their recorded trips. If not, automated emails were sent out instructing participants to check the GPS-accessibility of the app or reminding participants to validate their activities. Validation, however, was not a formal requirement for participation.

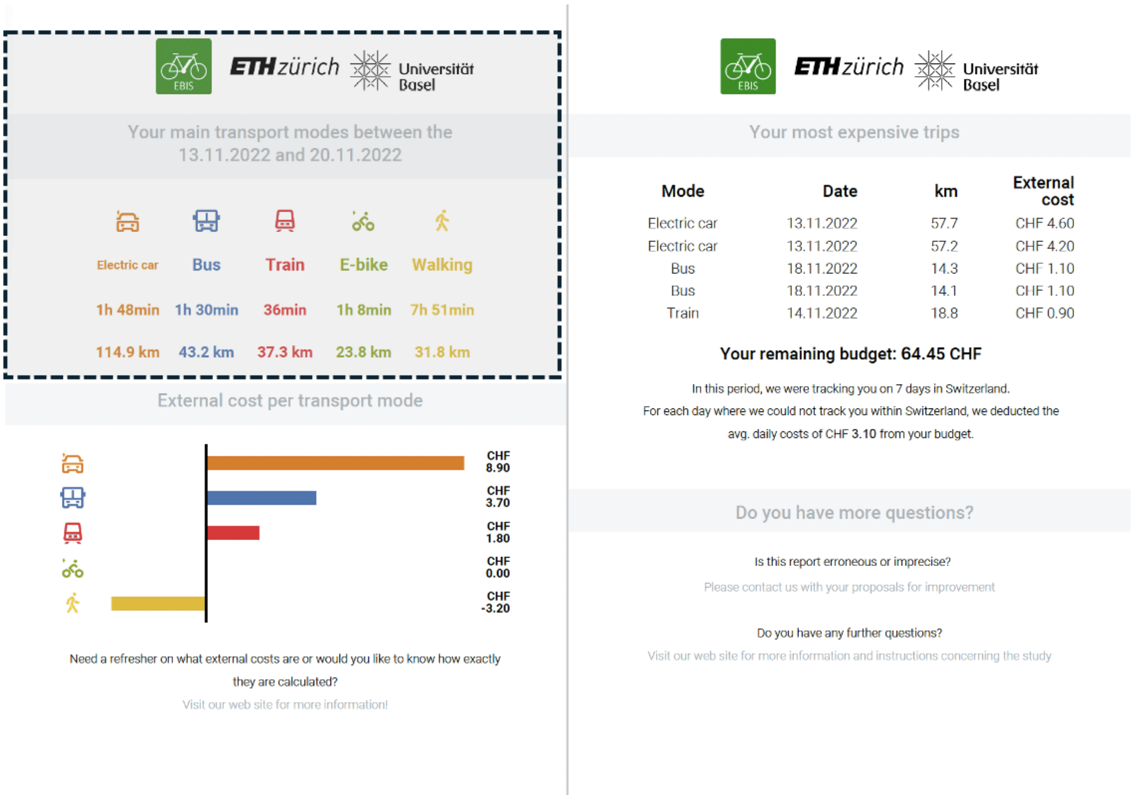
Participants in groups B and C concluded the official study period after Phase 1 and received an incentive payment of 20 Swiss francs[1] (the incentive was higher for participants in Group A, see Section 3.1.3). They were allowed and encouraged to continue tracking beyond this point, but no additional incentive payment was offered. The choice of 20 Swiss francs was made for budgetary reasons. Even with relatively low incentives, we were able to recruit the desired number of participants.

[1]Upon reaching the recruitment goals for group B and C (i.e. $\approx$ 850 participants each) we stopped promising an incentive payment. 924 individuals still agreed to enter the tracking study, leading to 45% and 20% of group B and C, respectively, participating without financial reward.

3.1.3 Randomized controlled trial

After Phase 1, participants in group A qualified for the RCT if they had successfully provided at least eight days of tracking data in Phase 1 (at least two days per week). If eligible, respondents were randomly allocated to the control or treatment group for Phase 2 without using any form of stratification. Information from the initial questionnaire was used to ensure that participants from the same household were allocated to the same group (to prevent treatment spillovers). Phase 2 was five weeks long. The length was set to ensure that a large enough sample size of user-days would be collected during the treatment phase to ensure statistical power.

Figure 3.3: Example of weekly reports received by participants



For the control group, the study continued with no changes from Phase 1. The weekly mobility reports continued to include the same information as during Phase 1 (dashed section in Fig. 3.3). Participants in the control group received a fixed and previously communicated incentive payment of 50 Swiss francs upon completion of the study.

The treatment group, on the other hand, were informed about a change in protocol:

- They received an overview of their personal external costs of travel generated throughout Phase 1 and how these were calculated.

- They received an individual travel budget based on their external costs of travel during Phase 1.
- They were informed that from now on, they would be charged for their external costs of travel from their travel budget. The amount left in their budget by the end of the study was theirs to keep.

The external costs consist of health, accident and environmental costs as in the official external costs in transport published by the Federal Office of Spatial Development of Switzerland (Metropia, 2019). The external accident cost for bicycles was the only modification made. This was meant to reflect a reality in which high quality cycling infrastructure leads to less deaths through accidents by bicycles. As shown by (Castro et al., 2018b), the fatality of bicycles in The Netherlands, the country with the lowest cycling fatality rate worldwide, is half of that in Switzerland. Accordingly, the external costs of accidents were reduced by this amount.

The average weekly travel budget of treated participants was equal to 120% of their average weekly external costs of travel from Phase 1. A 20% buffer was added to avoid participants ending up with a negative budget in the case that they had exceptionally low costs of travel in Phase 1. Despite the buffer, some participants generated substantially more externalities in Phase 2 than in Phase 1 and therefore exceeded their budget. In these cases, they were allocated one additional week's worth of budget (relative to their Phase 1) to keep them in the study. It was clearly communicated that this bonus is only given once.

During Phase 2, treated respondents received detailed reports about their externalities generated during that week (see Fig. 3.3). These reports included a differentiation of externalities by mode, a list of the "most expensive" trips, and the remaining travel budget. The reports were sent weekly until the end of the treatment period.

After completing Phase 2, all participants in Group A received a base incentive payment of 50 Swiss francs. In addition to the base incentive, treated participants were also paid out their remaining mobility budget. Like groups B and C, participants in group A were encouraged to continue tracking beyond the end of the study period but with no additional reward.

3.1.4 Additional questionnaires

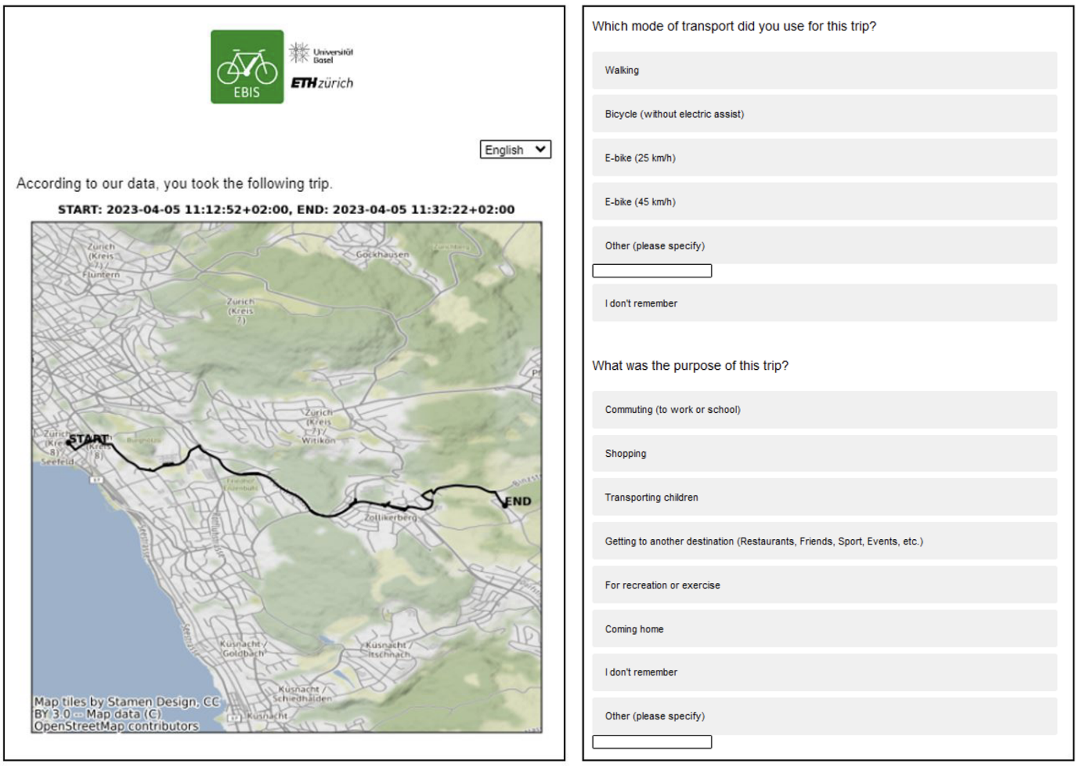
Retrospective survey: Two additional questionnaires were embedded into the EBIS study. The first one, the *retrospective survey*, was a Qualtrics-based mini survey sent out to participants in all groups after completion of Phase 1 as a part of either the intermediate (group A) or final (groups B and C) survey. The intermediate and final surveys had a response burden of 100; the retrospective survey contributed roughly 50 points to this score (Schmid and Axhausen, 2019).

Participants were asked about mode-substitution behavior based on up to five actual trips tracked during Stage 1.

For participants in groups A and B (E-bike owners), the presented trips consisted of their most recent, unique[2], E-bike trips with distance greater than two kilometers. Participants were asked which mode they would have chosen prior to having an E-bike available. For participants in group C (no E-bike ownership), the trips presented consisted of all modes. Participants were asked which mode they would have chosen if they had an E-bike available.

Specific trips of interest were visualized on a map (see Fig. 3.4). First, participants were asked if they remembered the given trip. If the participant remembered this trip, three additional questions followed. Here, participants were asked if they would have chosen an E-bike if one was available. For each respondent, a maximum of five trips were shown. The pipeline prioritized more recent trips to minimize recall losses.

Figure 3.4: Example of retrospective trip questionnaire

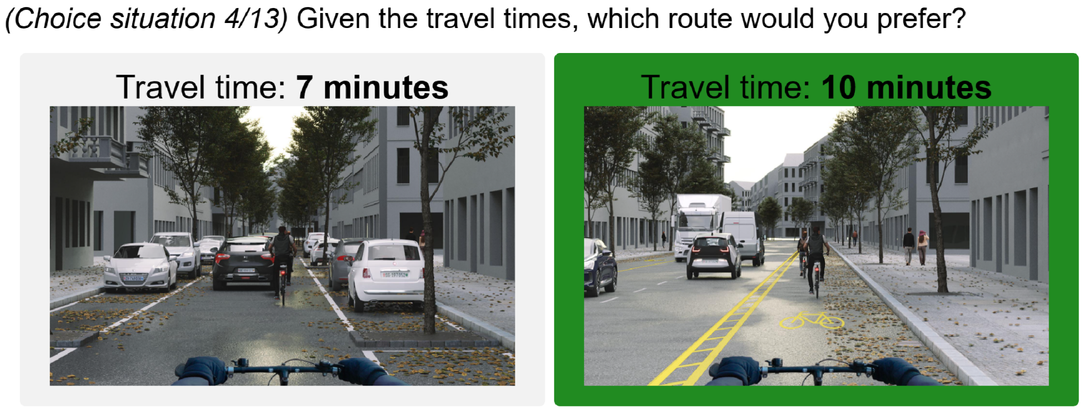


Stated Preference: The second survey was a stated preference (SP) survey to analyze preferences towards streetscape features affecting cyclists. Because RP data collected in the tracking phase was expected to capture preferences towards existing

[2]a trip was considered distinct if origin or destination were not within 500m of the origin and destination of another trip, respectively

cycling infrastructure, the SP survey included possible improvements to infrastructure that are not observable in Switzerland today. The experiment was divided into three blocks of choice situations: main streets compared to main streets, side streets compared to side streets, and main streets compared to side streets, and had a response burden of 110 (Schmid and Axhausen, 2019). Figure 3.5 shows an example of a choice situation from the survey. The choice situations varied travel times with cycling infrastructure attributes such as street markings, physical separation from traffic, and width of cycle lanes. The SP data will be used to estimate willingness-to-pay for cycling infrastructure in terms of travel time, as done in related literature Sener et al. (2009); Hardinghaus and Weschke (2022a); Börjesson and Eliasson (2012). Preliminary results of the experiment are available in Meyer de Freitas and Axhausen (2023).

Figure 3.5: Example of SP survey choice situation



3.2 Data

The study generated three primary datasets: user data containing socio-demographic information on the participants and their survey responses, trip data containing GPS tracks from stages and trips, and activity data containing GPS locations from stationary time periods. The user and trip data are described in detail below.

3.2.1 User data

The EBIS sample (n=3'940) skews male, highly educated, urban, and towards those with higher incomes. For example, 42% of EBIS participants have a monthly income above 12'000 CHF, compared to only 22% of bike or E-bike owners over age 14 in the (weighted) 2021 Swiss MTMC, a representative sample of the population (BFS, 2023). This is expected given the high cost of E-bikes, especially s-pedelecs, and the fact that s-pedelec owners are over-represented in the EBIS sample. However, even comparing to s-pedelec owners in the Swiss MTMC, EBIS participants still skew high-income: 48% of s-pedelec owners in the microcensus have monthly incomes over 8’000 CHF. Table 3.1 shows a demographic comparison of the EBIS sample (first column) to the comparable population in the MTMC (third column).

Table 3.1: Sociodemographic comparison of EBIS participants versus the MTMC

Attribute		EBIS unweighted	EBIS weighted	MTMC (e)bike owners
Gender	Female	0.38	0.49	0.49
	Male	0.62	0.51	0.51
Age	(14, 18]	0.01	0.03	0.05
	(19 - 30]	0.10	0.20	0.18
	(31 - 50]	0.45	0.38	0.38
	(51 - 65]	0.34	0.31	0.26
	(66 - 87]	0.10	0.08	0.14
Education level	Mandatory/General	0.05	0.08	0.23
	Vocational	0.38	0.39	0.49
	Higher Ed.	0.57	0.53	0.28
Urbanization	Rural	0.05	0.08	0.17
	Periurban	0.21	0.27	0.25
	Urban	0.73	0.65	0.58
Accessibility quantile	1	0.07	0.15	0.15
	2	0.23	0.28	0.28
	3	0.29	0.30	0.30
	4	0.40	0.27	0.27
Household income	4’000 CHF or less	0.03	0.04	0.08
	4’000 CHF - 8’000 CHF	0.22	0.23	0.28
	8’000 - 12’000 CHF	0.29	0.27	0.24
	12’000 - 16’000 CHF	0.28	0.28	0.12
	16’000 CHF or more	0.14	0.13	0.10
	Prefer not to say	0.02	0.03	0.08
	I don’t know	0.01	0.02	0.10
Nationality	Swiss	0.82	0.84	0.77
	Other	0.18	0.16	0.23
Operating System	iOS	0.57	0.57	
	Android	0.43	0.43	
Mobility tool	Car	0.62	0.60	0.86
	National season ticket	0.15	0.17	0.09
	Half fare travel card	0.70	0.68	0.38
	Regional season ticket	0.09	0.10	0.10
	Bike (not electric)	0.82	0.82	0.91
	E-bike	0.37	0.37	0.28
	S-pedelec	0.35	0.34	0.05

Note: EBIS participants (n = 3’940) compared to bike and E-bike owners over age 14 in the 2021 MTMC, weighted values (n = 36’241) (BFS, 2023)

The data was weighted using iterative proportional fitting (IPF) to match bike and E-bike owners over age 14 in the Swiss population. This target population was chosen to align with the imposed criteria for the EBIS participants. Four variables were chosen for weighting: gender, age, education, and public transportation accessibility quantile of home location (Bundesamt für Raumentwicklung (ARE), 2022). As information on the exact home locations was not available, home locations were imputed as the most frequent location for the first trip of each day throughout the tracking period. The imputed value aligned with the reported home postal code for 97% of people. Despite not aligning perfectly, the most common location for starting one's day was assumed a representative location at which to measure accessibility. Due to relatively small sample sizes among some subgroups, weights were capped at four to avoid weighting any one individual too highly.

The second column of Table 3.1 shows demographics of the weighted sample. After weighting, the EBIS population is fairly representative of the MTMC, although discrepancies remain regarding the ownership rates of different bike types and education level. Bike type could not be weighted on due to low s-pedelec ownership rates among the Swiss Microcensus. Subsequent analyses should take the differing mobility tool ownership rates into account. In addition, despite including education level in the IPF, the EBIS sample still severely overrepresents those with a university degree and underrepresents those with only mandatory education. Future studies should try to specifically target those with only mandatory education in order to collect a more representative sample.

3.2.2 Trip data

The EBIS study includes GPS mobility data from over 324'000 person-days and 2.8 million stages within Switzerland between September 2022 and August 2023. Out of the 2.8 million stages, over 500 thousand were made by bike or E-bike.

GPS tracks from the Catch-my-Day app are returned in stages (unlinked trips), where a stage is a continuous movement with one mode of transport as defined by Axhausen (2007). However, when working with GPS-track data, the data of interest is more often sequences of stages between origin-destination pairs, referred to here as trips. As such, the stages need to be aggregated into trips. For example, a trip to work may consist of walking to the bus stop (stage 1), taking the bus (stage 2), and then walking from the bus stop to the office (stage 3). Most studies take a time-based approach to trip identification (Schuessler and Axhausen, 2009; Stopher et al., 2008; Gong et al., 2012; Wolf et al., 2004). For example, trajectories are separated into unique trips when the stationary activity between them exceeds a threshold that can range from 120 seconds (Schuessler and Axhausen, 2009; Stopher et al., 2008) to 300 seconds (Wolf et al., 2004). See Safi et al. (2016) for a summary of time-based approaches taken in the literature.

This approach can severely misrepresent public transportation (PT) waits and transfers, many of which are longer than the imposed threshold. As the Catch-my-Day app allowed users to manually enter the purpose of stationary activities, the potential misrepresentation of PT waits can be quantified. Using PT stop geodata (Specialist Office Open Data, 2023), we identified stationary activities which happened at PT stops, before PT stages, and with user-validated purpose of "wait". Of these stationary activities, 63% had a length of over 300 seconds (the upper bound for the threshold used in most studies, see Safi et al. (2016)) and thereby would have been misrepresented by a 300-second threshold.

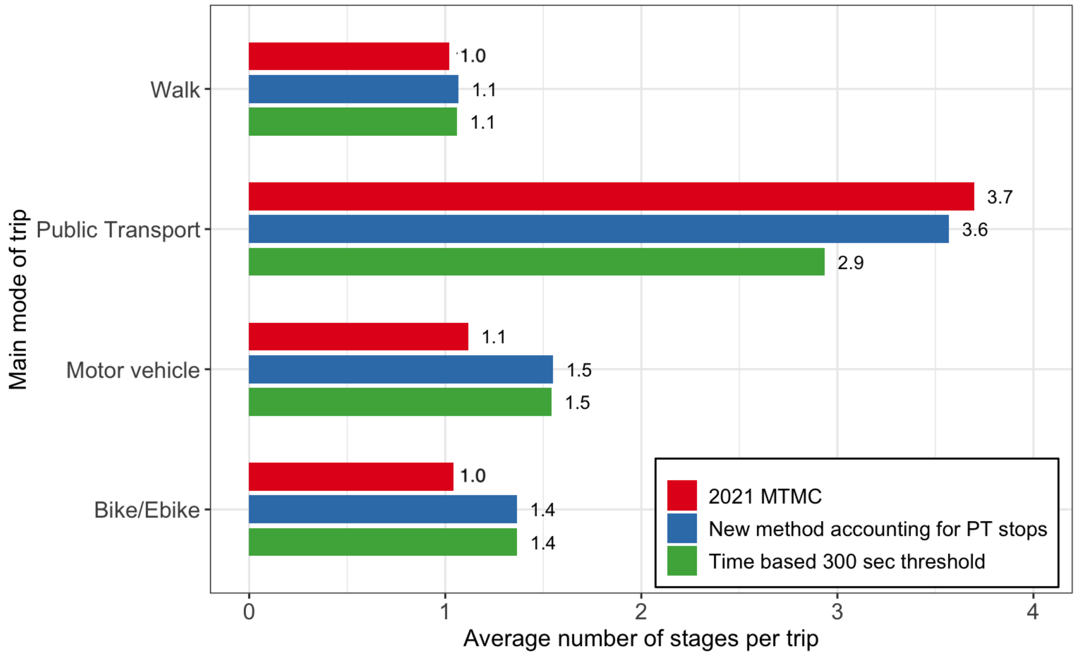
The challenge of correctly differentiating between public transport transfers and short activities is not new: a body of literature exists which specifically aims to identify public transport transfers, often from fare card data such as by Seaborn et al. (2009) and Nassir et al. (2015), though also location based data as done by Carrel et al. (2015) and Marra et al. (2019). These approaches are more nuanced and accurate than the time-based approach typically taken in GPS-tracking literature, however, they rely on knowledge of public-transport time tables which were not integrated into the EBIS data.

We aggregated tracks using a novel strategy which accounted for a distinction between PT waits and other stationary activities by utilizing the user entered purpose of the activity along with the geodata on PT stops. Suspected PT waits - stationary activities which happened at PT stops, before PT stages, and with either a user-validated purpose of "wait" or with no specific user-entered purpose - were identified. These suspected PT waits were aggregated to the previous stage if there was less than a one-hour gap between stages. The maximum transfer time of one hour was chosen as in Nassir et al. (2015) and by inspection of the data. For all other stages, including those of modes other than PT or those happening *after* a PT stage (as opposed to before), a time-based approach with a 300-second threshold was applied.

To test the new methodology, the average number of stages per trip for each main mode of travel was compared to the values found when applying a time-based 300 second methodology, and to the reported values from the 2021 MTMC (which serve as a baseline). The results are shown in Figure 3.6. As expected, the new methodology does a better job at matching the MTMC data for PT trips than the purely time-based methodology does: the time-based methodology averages only 2.9 stages per PT trip, which is too low because any PT trip should have at minimum three stages (an access and egress stage at either end, plus the PT stage itself). For bike and motor vehicle trips, the average number of stages per trip is higher in the EBIS data than in the MTMC data. This is an expected consequence of the under-reporting of short stages, such as walking to and from vehicle parking, in conventional travel diaries (Janzen et al., 2018; Stopher et al., 2007) and therefore illustrates a strength of the EBIS data. The value slightly above one stage per trip for walking trips is a likely consequence of GPS tracking pausing at short stops such as red lights. Even if these pauses split some trips into multiple stages, this is not of concern after aggregating the stages to the trip level.

As with any approach, there exist limitations. It is possible that short activities that took place near PT stops, such as grocery shopping at a train station, have been erroneously classified as PT waits. However, the use of user-entered activity purpose data helps mitigate this risk: stationary activities with a user-entered purpose other than "wait" were never classified as PT waits. Although entering activity purpose was optional, across all users and activities 60% of stationary activities were labeled with a purpose.

Figure 3.6: Average number of stages per trip, by main-mode of travel



Note: Main mode is defined as the mode with the longest combined distance.

3.3 Results

3.3.1 Recruitment

Each recruitment channel contained a distinct link to the introductory survey, which enabled identifying participants by recruitment channel. A few caveats exist: for written invitations (i.e. letters and flyers) this information was embedded in a QR-code. To increase accessibility for non-tech savvy individuals, a short link to the survey was also printed in clear text. Because the written link was identical for the letters and the fliers, participants who entered via the link cannot be clearly differentiated. In addition, participants could open the survey from the study website. Therefore, the "website" channel could contain individuals from all recruitment channels who wanted to first read the website. Finally, it remains unknown how many recruitment channels an individual was exposed to prior to opening the link.

Table 3.2: Study enrollment and progress summary for EBIS participants by recruitment channel

Recruitment channel	Reached (#)	Started survey (#)	Started tracking (#)	Started tracking (%)	Finished study (#)	Finished study (%)	Finished reached (%)
Personal E-Mail	8'262	4'326	1'466	33.89	1'369	31.65	16.57
Social media	*[Unknown]*	1'004	247	24.60	227	22.61	-
Newsletter	230'000	759	176	23.19	169	22.27	0.07
Website / Weblink	*[Unknown]*	2'910	714	24.54	629	21.62	-
Flyer	1'000	50	11	22.00	10	20.00	1.00
Letter from canton	13'800	2'246	520	23.15	441	19.63	3.20
Intranet advert	*[Unknown]*	905	175	19.34	148	16.35	-
Unknown	*[Unknown]*	177	26	14.69	21	11.86	-
Link panel	12'978	4'824	605	12.54	557	11.55	4.29
Total	-	17'201	3'940	22.91	3'571	20.76	-

Note: Percentage columns indicate share w.r.t the "started survey" column, except for the final 'Finished reached' which shows percentage of those reached who finished the study. Recruitment channel information was received via custom links. However, in 177 cases this information was missing, likely due to incomplete entry of the link.

Table 3.2 shows the number of individuals who were contacted, who started the introductory survey, who downloaded the app and started tracking, and who completed the final survey. The statistics are presented for each recruitment channel separately and ordered by the number of individuals starting to track for the study. Overall, of the 17'201 individuals who started the introductory survey, 20.76% completed the entire study.

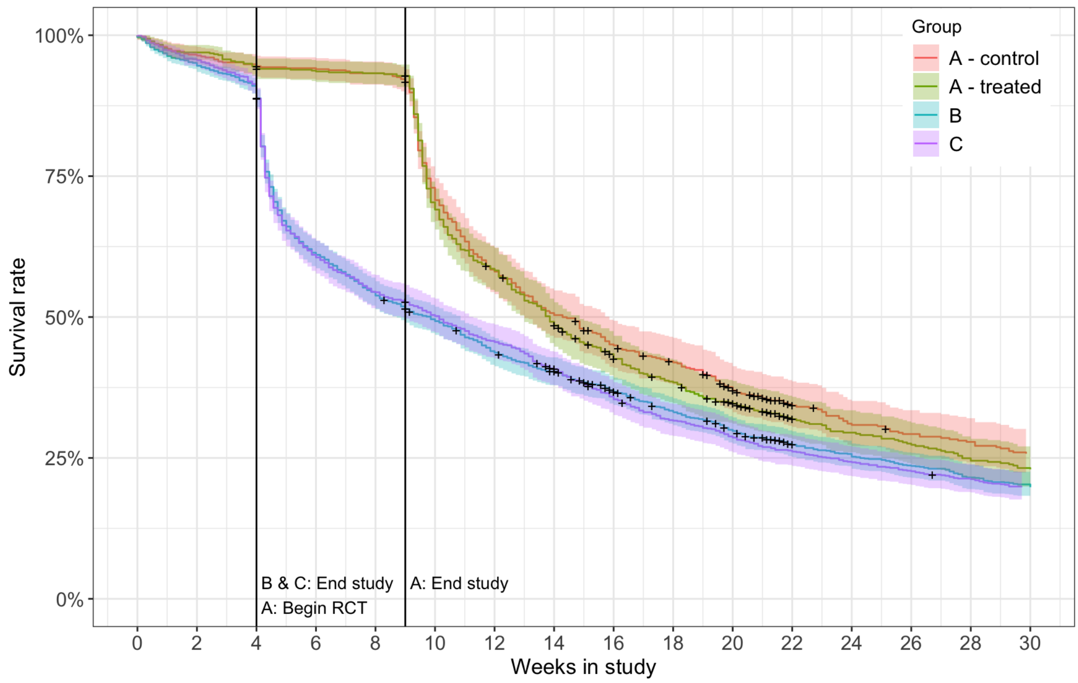
The recruitment channels reached different numbers and types of participants. Invitation by a personal e-mail proved to be the most effective recruitment strategy, not in the number of participants, but also in the share of individuals finishing the study. Recruitment through the Link panel successfully led people to open the first survey, but a rather low share of them was willing to participate and finish the tracking study. The remaining recruitment channels were similar in their success rates - with all having about 20% finishing the study. Letters from cantons and the Link panel specifically targeted group A individuals and hence reached a higher share of group A participants, whereas the social media campaign was less successful in reaching this population.

3.3.2 Participant engagement and retention

Of the 17'201 people who started the introductory survey, 34.4% qualified for the study. Not agreeing to be tracked, for example due to concerns around phone battery life, was the most common reason for not qualifying. Out of those who qualified and agreed to participate, 66.5% began tracking, which is similar to the rate found in the MOBIS study (Molloy et al., 2023). The others either failed to install the app or to activate the tracking. Of those who successfully recorded a first track, 90.6% successfully completed the tracking period, meaning four weeks for groups B and C (Phase 1) and nine weeks for group A (Phase 1 and 2). Despite differing study period lengths, the study completion rates are very similar across groups.

To explore the retention rate of participants over the course of the study, we conducted a Kaplan-Meier survival analysis similar to Molloy et al. (2023). Figure 3.7 shows participant retention over time by group, with vertical lines at week four (study period length for groups B and C) and nine (study period length for group A). Approximately 90% of individuals are tracking at the end of their study periods. After the end of the official study period, we see a sharp decline as participants were told they could delete the app, but even half a year out approximately 25% of participants were still voluntarily contributing their tracking data.

Figure 3.7: Kaplan-Meier survival curve of EBIS participants



Note: Kaplan-Meier survival curve by group to predict discontinuation of tracking of EBIS participants recruited between September 2022 and January 2023. The cross indicates censoring of participants.

We see no visual difference in retention rates between the treatment and control groups in the RCT. This was confirmed by a Cox-proportional hazards model on participant retention across the study period, which found no significant difference in survival rates during the study period for the treatment group versus the control group. In addition, no significant difference in retention during the study period was found by recruitment source, allaying concerns that those who chose to sign up after seeing the study advertised on social media or in a cycling newsletter may be more invested than those recruited through more traditional methods such as the cantonal invitation letters. In fact, the only variable found to correlate with dropout rates during the 9-week study was the operating system of the user's mobile phone, with iPhones owners dropping out at lower rates (hazard ratio 0.6). This aligns with findings from the MOBIS study, which experienced the same discrepancy in dropout rates by phone type and noted difficulties by Android users in getting the app to function properly (Molloy et al., 2023).

Table 3.3: Cox proportional-hazard model to predict discontinuation of tracking. Coefficient estimates and standard errors.

	Groups B and C	Group A
iOS operating system (vs Android)	-0.23***	-0.31***
	(0.04)	(0.07)
Age	-0.20***	-0.28***
	(0.05)	(0.07)
Higher education (vs no higher education)	-0.12**	-0.04
	(0.05)	(0.07)
Recruitment channel: Intranet advert	0.45	0.43
	(0.39)	(1.02)
Recruitment channel: Cantonal invitation	0.54	0.51
	(0.39)	(1.01)
Recruitment channnel: Link institute	0.17	0.17
	(0.39)	(1.00)
Recruitment channel: Newsletter	0.31	0.14
	(0.39)	(1.02)
Recruitment channel: Personal email	0.31	0.35
	(0.38)	(1.00)
Recruitment channel: Social Media	0.34	0.27
	(0.39)	(1.02)
Recruitment channel: Unknown	0.09	0.13
	(0.49)	(1.05)
Recruitment channel: Website or web link	0.39	0.37
	(0.38)	(1.01)
Treatment group (vs control)		0.07
		(0.07)
AIC	31'175.26	11'848.02
R^2	0.03	0.05
Max. R^2	1.00	1.00
Num. events	2'180	931
Num. obs.	2'653	1'232
Missings	3	52
PH test	0.78	0.45

Note: ***p<0.001; **p<0.01; *p<0.05.

Since participants were encouraged to continue tracking past the end of the official study period, we were also able to investigate longer term dropout rates. Considering the collection of GPS tracking data past the official study end, several sociodemographic factors were found to correlate significantly with continued participation rates. These factors can be seen in Table 3.3. Since the study period length was different for group A compared to groups B and C, the groups were not combined for post-study survival analysis. Contrary to expectations, older people were more likely to continue tracking for a longer time period. Those with iOS operating systems and higher education were also more likely to continue tracking for longer. Effects of recruitment channel and treatment group are insignificant. Additional factors including gender, income, and household size were also tested for their effect on post-study participation rates, but no significant effects were found.

3.3.3 Travel behavior

As seen in Table 3.4, the EBIS population appears more active than the comparable population in the Swiss MTMC. EBIS participants completed on average 4.7 origin-destination trips per day, compared to 2.9 in the MTMC, and travel on average 53.10 person-kilometers a day, 64% more than 32.5 in the MTMC. Although significantly higher than the MTMC, these values are similar to those seen in other GPS-tracking studies in Switzerland (Hintermann et al. (2025)).

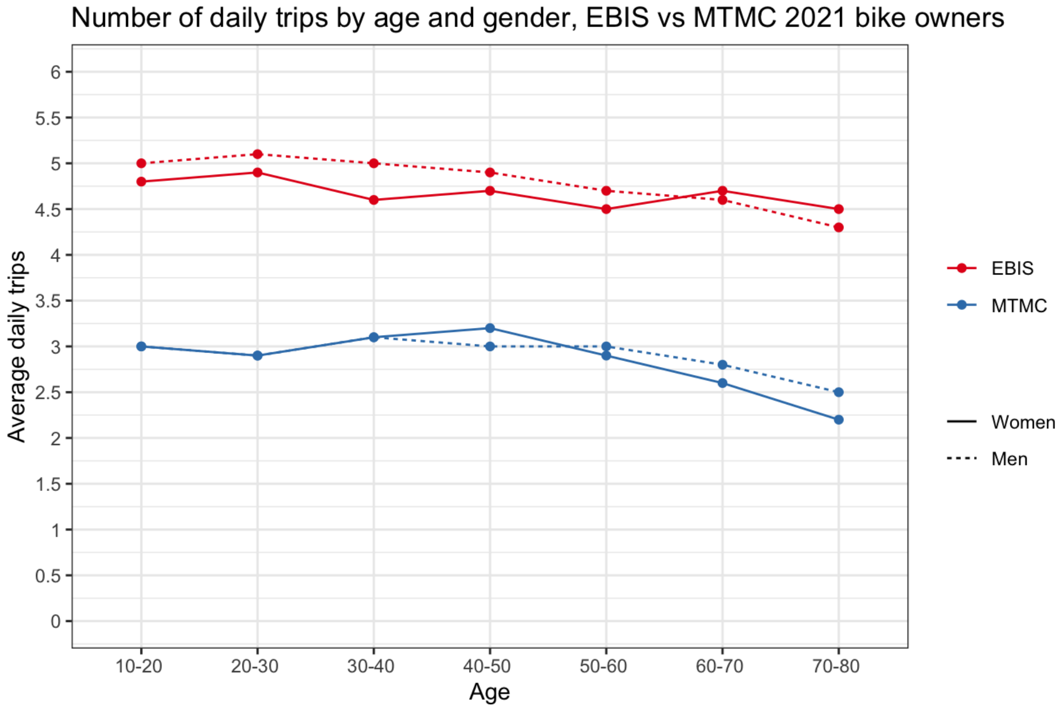
Table 3.4: Daily travel averages for EBIS versus the 2021 MTMC

	Daily average per person	EBIS weighted	MTMC (e)bike owners
1	Trips/day	4.70	2.90
2	Stages/day	7.70	4.00
3	Travel distance (km)/day	53.20	32.50
4	Travel time (min)/day	104.10	84.70

Note: MTMC data averaged from bike and ebike owners over age 14. Treated group A participants during treatment period are excluded from averages (BFS, 2023). Averaged across all days (weekdays and weekends).

It is also possible that the EBIS population actually is more active than the public. Some evidence is seen in Figure 3.8: among the MTMC sample the average number of daily trips decreases as people age, whereas among the EBIS participants the average number of daily trips remains relatively constant across age groups, especially for women. This coincides with existing research that shows a positive correlation between cycling or E-biking and the activity space area of older adults (Van Cauwenberg et al., 2019; Leger et al., 2019; Tsunoda et al., 2015; Van Cauwenberg et al., 2022). The EBIS travel behavior suggests that all cyclists, not just older adults, have a larger-than-average activity space (travel behavior was compared to bike owners in the MTMC to try to compare similar groups, however, bike owners in the MTMC may not be regular cyclists). Furthermore, in the EBIS sample, only 6% of the tracked days show zero distance travelled, which is in line with the literature (Madre et al., 2007; Hubert et al., 2008), but low compared to the numbers of 17% and 11% found in the MTMC of 2021 and 2015, although the MTMC values may be inflated by soft refusers (BFS, 2023). Lastly, it is possible that individuals who choose to participate in a GPS-tracking study on cycling are unrepresentative of the public in ways that are difficult to quantify. For example, those who are active in their daily lives may be more interested in learning about their travel behavior or contributing to mobility research, leading to potential self-selection bias.

Figure 3.8: Average daily trips by age group and gender

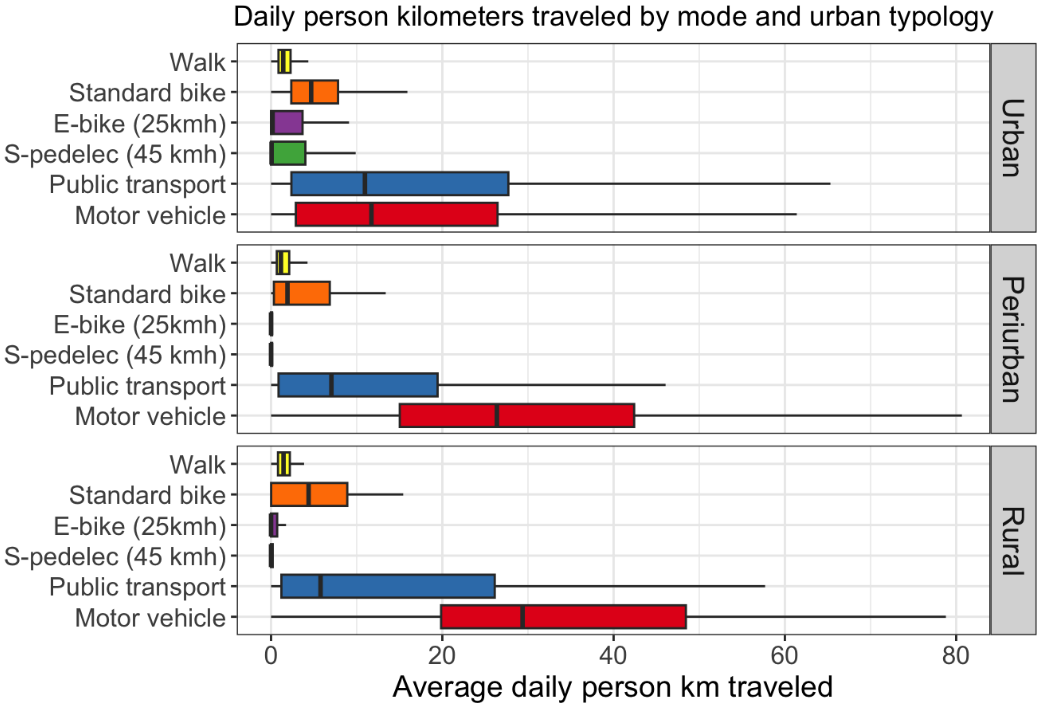


Note: EBIS participants versus bike and ebike owners over age 14 in the 2021 MTMC. Weekend and weekdays included. Treated group A participants during treatment period are excluded from averages (BFS, 2023).

A modal split of average person-kilometers traveled by urban topology is shown in Figure 3.9. The bike, E-bike, and s-pedelec averages are calculated among owners of the given bicycle type. Across all typologies, s-pedelec owners travel on average further distances by bike than owners of standard bicycles or E-bikes, which makes sense given their higher speeds. Interestingly, regular cyclists tend to travel further distances by bicycle than owners of regular E-bikes in all urban typologies. This corroborates prior findings by Damant-Sirois et al. (2014) that cycling typologies exist among bike-owners: steadfast bike commuters versus those who own an E-bike, but do not use it as a default mode of travel.

Finally, we show a brief overview of the seasonality of travel behavior in Figure 3.11 and Figure 3.10. Figure 3.11a shows total average travel distance by EBIS group, whereas Fig. 3.11b shows average car distance by EBIS group and Fig. 3.11c shows bike distance by EBIS group. Seasonality of pkm traveled by bike type rather than group is shown in Figure 3.10. Future research on the EBIS project will investigate mode choice more deeply, including the effect of seasonality. Our preliminary overview

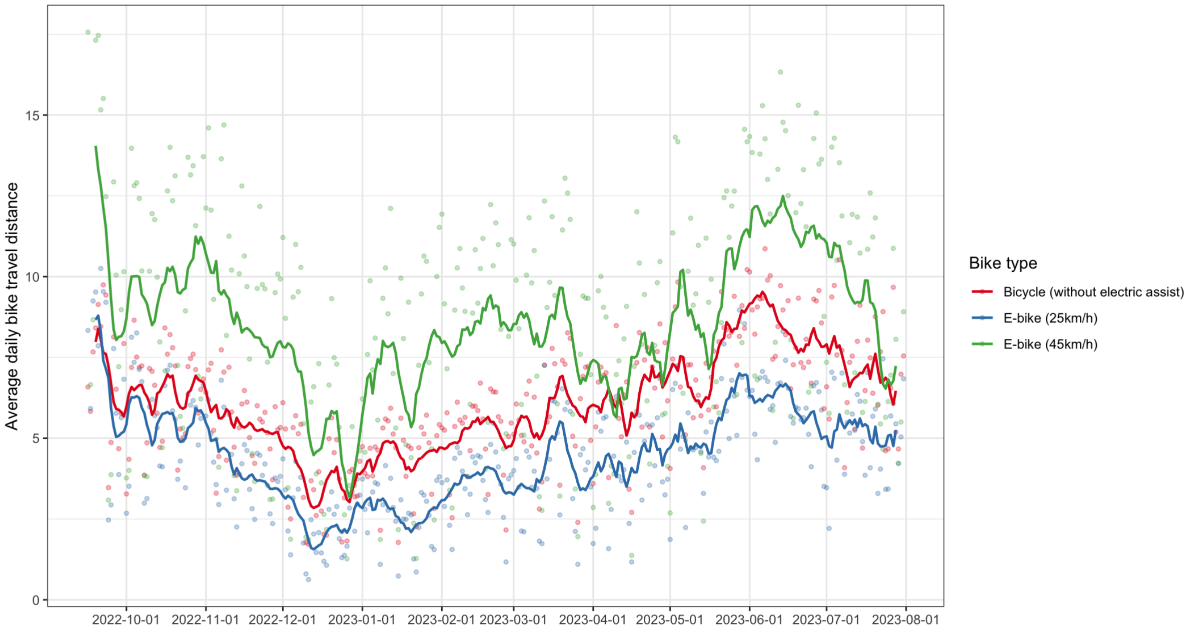
Figure 3.9: Daily person kilometers traveled by EBIS participants, split by mode and urban typology.



Note: Treated group A participants during treatment period are excluded from averages.

shows several expected patterns. Participants in Group A, who were allotted to group A due to car availability, have higher average car travel distance than participants in groups B or C. E-bikers without regular car access tend to travel farther distances by bike than regular cyclists or E-bikers who do have a car available. However, as seen in Figure 3.11a, the average distance travelled across all modes does not differ much between groups. Also as expected, bike pkm travelled shows the largest seasonality effect, with more than twice as many pkm travelled on average in the summer months than in the winter months. All three groups show a spike in car travel around the Christmas holiday, when people travel to be with family, and a subsequent drop in travel in early January, before people have returned back to work. In Figure 3.10 we see the same seasonality trend of cyclists evident in Fig. 3.11c and the pkm differences by bike type as evident in Figure 3.9 and discussed above: S-pedelecs cover the most pkm by bike, followed by regular cyclists and regular E-bikes.

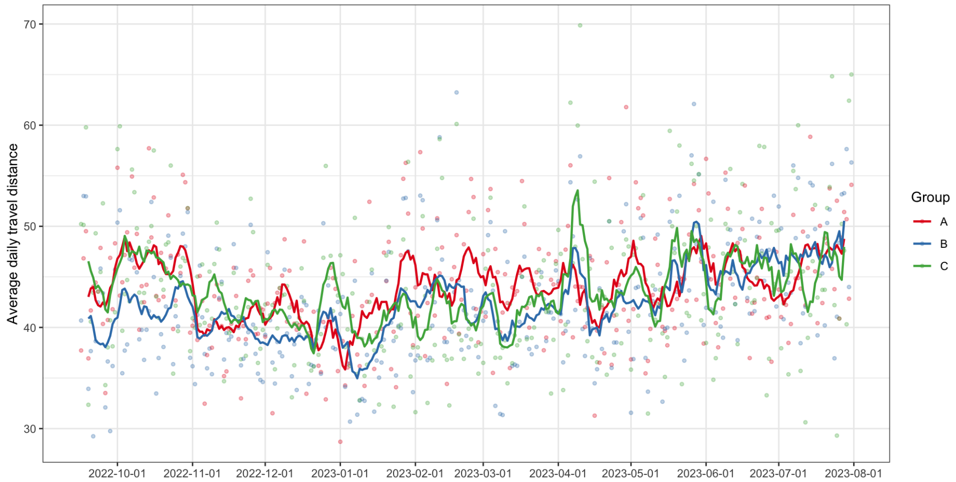
Figure 3.10: Seasonality of travel by bike type



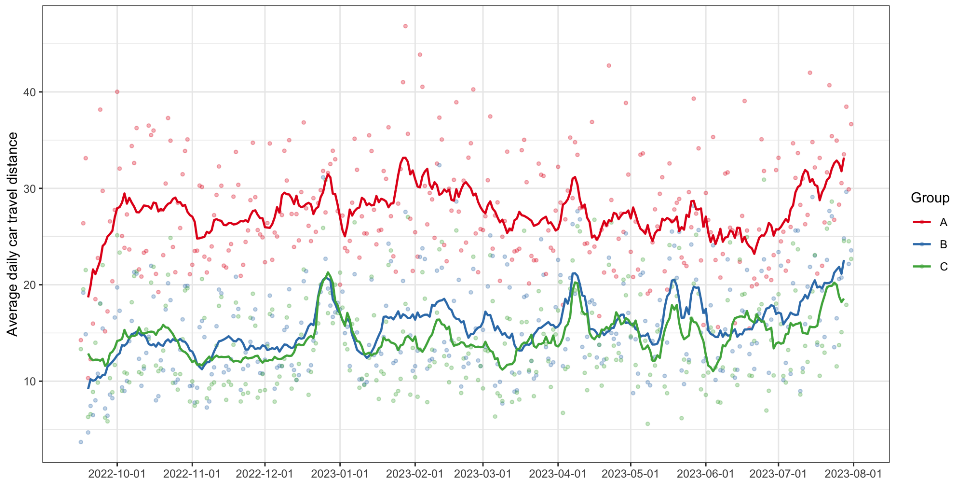
Note: Treated group A participants during treatment period are excluded from averages.

Figure 3.11: Seasonality of travel by mode and group

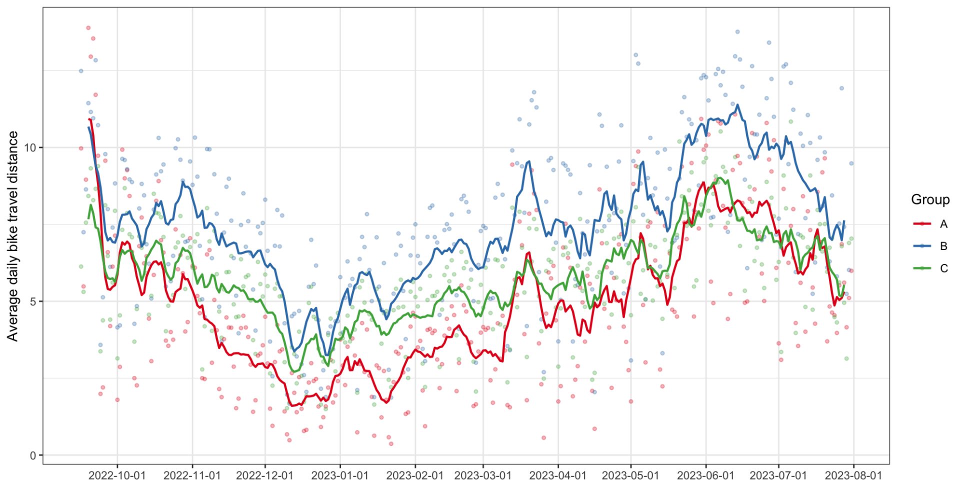
(a) Average total travel distance



(b) Average total car distance



(c) Average total bike distance



Note: Treated group A participants during treatment period are excluded from averages.

4 Route choice

The route choice-relevant data collected throughout the EBIS study includes revealed preference (RP) and stated preference (SP) data. These types of data are collected and analyzed very differently, and we therefore discuss the corresponding research separately.

For the RP data, we analyze the data separately for different urban regions (Zurich, Aarau and Basel).

4.1 Revealed preferences

The scientific community has developed numerous approaches to the problem of modeling route choices based on RP data. Following Fosgerau et al. (2013), one can differentiate between *path-based* and *link-based* approaches (excluding more recent machine-learning based models).

The majority of published models are path-based and many different model specifications have been presented. Path-based models estimate model parameters by comparing observed routes with un-chosen alternatives. They involve a method to generate these un-chosen alternatives, i.e. a choice set, and typically make the assumption that the generated choice set includes the actual true alternatives. Following Prashker and Bekhor (2004), the models can be classified into three categories, depending on how they deal with the problem of correlated routes and the consequent violation of assuming independent and identically distributed (IID) error terms in Multinomial Logit (MNL) models. The most common types are MNL-correction models. These models add a correction term to the deterministic part of the utility function in order to approximate the effect of the correlation. Examples include the PSL (Ben-Akiva and Ramming, 1998) and the C-Logit (Cascetta et al., 1996). The MNL structure gives these models a closed-form solution and the computation of the corrections terms is relatively straight-forward. Some recent works deal with improving these correction terms to applications in large-scale networks where choice sets have many overlapping and infeasible alternatives (see e.g. Duncan et al. (2020, 2021)). Examples of PSLs applied to modeling cyclists route choice include Broach et al. (2012); Menghini et al. (2010); Hood et al. (2011); Casello and Usyukov (2014); Ton et al. (2017); Scott et al. (2021); Bernardi et al. (2018); Fitch and Handy (2020); Khatri et al. (2016); Skov-Petersen et al. (2018); Shah and Cherry (2021); Prato et al. (2018); Meister et al. (2023). The results are mostly intuitive and consensual. Cyclists generally prefer shorter routes, ideally with some sort of cycling infrastructure and scenic environments. They tend to avoid positive gradients, mixed traffic conditions (with motorized- or foot traffic), as well as traffic signals and intersections.

Modeling framework The path-based models estimated in this study have the form of PSLs. These have a well-known MNL structure where the utility $U_{it} = V_{it} + \varepsilon_{it}$ is composed of a deterministic part V_{it} and a random error term ε_{it} which is IID extreme value type I. The probability that a decision maker chooses alternative i from the choice set C_t in the choice situation t is given by:

$$P_{it} = \frac{e^{V_{it}}}{\sum_{j \in Ct} e^{V_{jt}}} \tag{4.1}$$

Independent of the applied choice set generation algorithm, the utility function includes the Path-Size (PS) correction term which accounts for the correlation between alternatives. The PS term is defined as:

$$PS_{it} = \sum_{a \in T_i} \frac{l_a}{L_i} \frac{1}{\sum_{j \in C_t} \delta_{aj}} \tag{4.2}$$

where l_a represents the length of a certain link a, L_i is the total length of the route i, T_i is the set of all links contained in route i, and δ_{aj} is an indicator that is 1 if link a is included in route j, and 0 otherwise. The models are estimated using the $mixl$ package (Molloy et al., 2021a) through maximum likelihood estimation.

Choice set generation The MH algorithm has been proposed by Flötteröd and Bierlaire (2013) for generating paths from a given network. It can be considered a *sampling* approach, as it does not make the assumption that the generated alternatives represent the true choice set. It assumes a universal choice set including all feasible paths, and requires an additional correction term in the utility function to account for the sampling protocol. The MH algorithm is based on a Markov-chain Monte-Carlo method and used to sample from, typically multi-dimensional, distributions that are unknown or infeasible to sample directly from. In a route choice context, the distribution of interest are those that represent the probability of a certain path being chosen by a traveler. For a given OD, the algorithm starts by generating an initial route candidate, typically the least-cost path. For a predefined number of iterations, the algorithm will generate a new path by randomly inserting new nodes along the path, i.e. either generating a shortcut or detour. Each of the generated route candidates is either accepted or rejected, i.e. added to the choice set, based on the likelihood of the respective path being chosen under the assumed preferences of the traveler (e.g. travel time, infrastructure, etc.). For a given choice set, the frequencies of each path's occurrence approximates towards the preferences specified in the cost function. A major advantage of applying the MH algorithm to sample paths, is the redundancy of specifying a choice set size. The algorithm is disadvantageous w.r.t. the additional computational load introduced through the generation of candidates. Furthermore, the algorithm does not scale well to larger networks as the number of iterations required to generate heterogeneous choice set increases proportionally. The resulting deterministic part of the utility function is given by:

$$V_{it} = \beta^{length} \cdot x_{it}^{length} + \sum_{s \in LOS} \beta^s \cdot x_{it}^s + \beta^{PS} \cdot \mathit{ln}(PS_{it}) + \mathit{ln}(\vartheta_i) \tag{4.3}$$

where i denotes the alternative and t the choice situation. β^s represent the estimated parameters for each level-of-service (LOS) attribute s, with their corresponding values x_{it}^s. PS_{it} is the PS correction term with its corresponding parameter β^{PS}. $\vartheta_i = k_i/q_i$, represent the sampling correction where k_i is the sampling frequency and q_i is normalized weight for each respective route in the choice set.

The following sections present the results for the three main study areas individually. Please note that the sections for each study area is designed as stand-alone chapter. The last section concludes with a comparison of policy-relevant econometric indicators across the three study areas.

4.1.1 Zurich

Sample composition The sample consists of individuals that provided user-validated cycling trips (validation of detected trips through the Catch-my-Day app was not required but encouraged, see Chapter 3.3) that could be successfully processed for the respective modeling approach (i.e. mostly related to map matching). The differentiation between different bike types is based on the initial questionnaire, where respondents had to state which bike type they use the most. The Catch-my-Day app cannot automatically detect differences between regular E-bikes and S-pedelecs. Table 4.1 presents the socio-demographics attributes of the complete sample, the bike-specific sub-samples, and the census (MTMC) reference (BFS, 2023).

Table 4.1: Socio-demographic attributes of the Zurich sample with MTMC reference.

Attribute		Bicycle (n = 371)	E-bike (n = 165)	S-pedelec (n = 345)	Total (n = 881)	MTMC
Gender	Male	0.68	0.46	0.76	0.67	0.49
	Female	0.32	0.54	0.24	0.31	0.51
Age	< 40	0.44	0.26	0.17	0.30	0.41
	40 - 60	0.46	0.51	0.71	0.57	0.33
	> 60	0.1	0.23	0.12	0.13	0.26
Income	N/A	0.02	0.03	0.03	0.02	0.21
	Low (< 4kCHF)	0.06	0.03	0.00	0.03	0.09
	Mid (4-12kCHF)	0.49	0.48	0.42	0.46	0.58
	High (> 12kCHF)	0.45	0.46	0.55	0.49	0.12
Education	Mandatory	0.05	0.04	0.01	0.01	0.23
	Secondary	0.21	0.35	0.37	0.31	0.49
	Higher	0.74	0.61	0.62	0.68	0.28

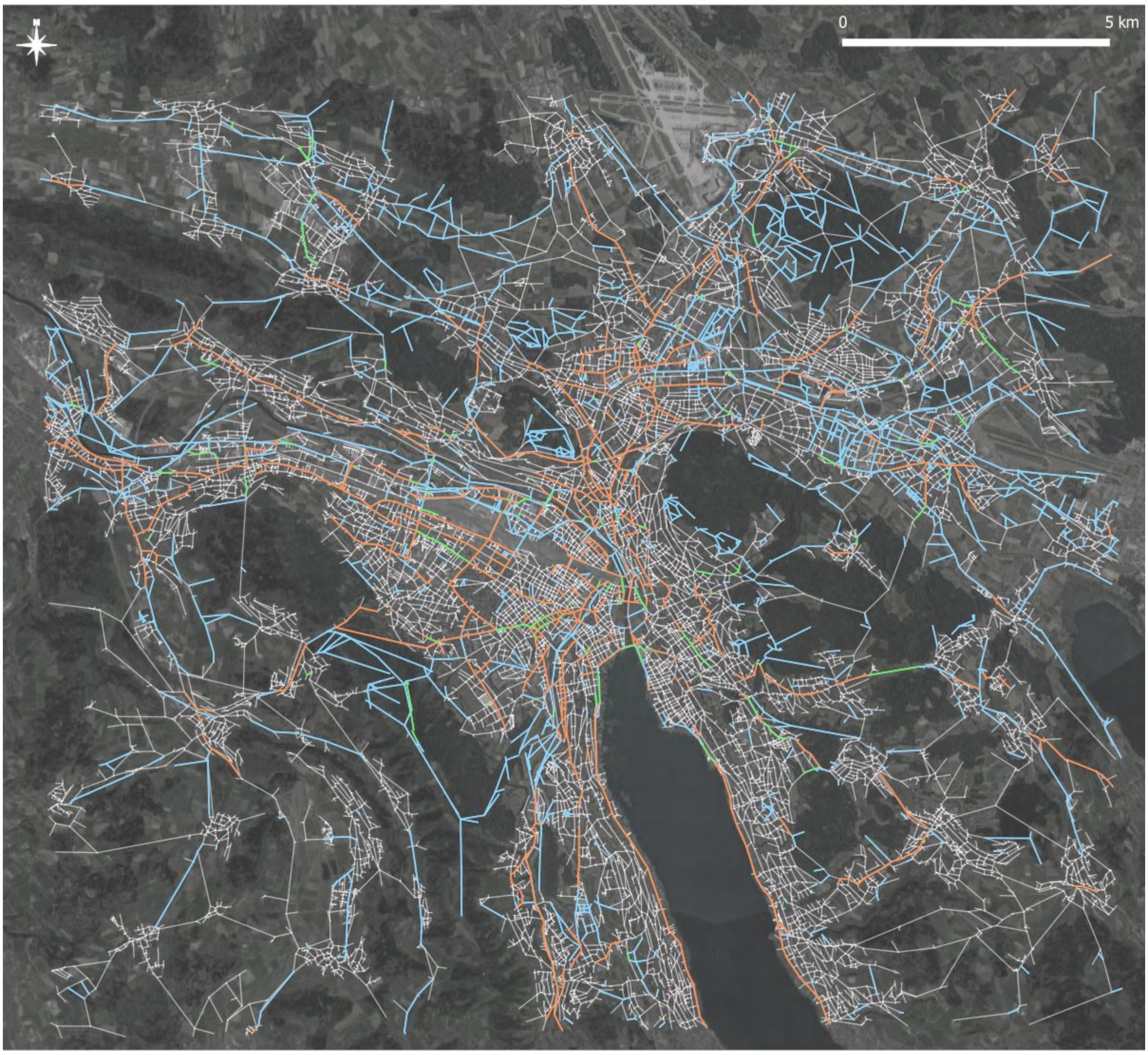
The complete sample consists of 881 individuals, with the non-regular bike users comprising around 60%. It can be seen that, compared to the census reference, the sample is biased towards being rather male, older, better educated and with higher income. Considering the sub-samples, one can see that the S-pedelec users are even stronger biased towards being male, older and with higher income. The patterns across the different sub-samples are aligned with the general literature on types of cyclists and bike-ownership. As shown in previous Swiss studies (Molloy et al., 2022), cyclists are typically better educated, whereas this overlaps with the general education bias of academic GPS-tracking studies. E-bikes and especially S-pedelecs usually represent a substantial monetary investment and are typically more accessible to higher income groups and/or older cohorts.

Network The network is generated using the SNMAN package (Ballo and Axhausen, 2023). The package uses an Open-Street-Map (OSM) network as basis and then simplifies it by merging parallel edges to center-lines (i.e. one edge for a multi-modal street section) and consolidating intersections. The simplification is crucial to avoid ambiguities when matching noisy GPS traces to the network. Furthermore, the simplification reduces the network complexity, which in turn substantially reduces the time required to process the comparably large amounts of data collected in this study. The resulting network is shown in Figure 4.1.

The network covers an area of approx. 350km^2 and includes the whole municipality of the city of Zurich. From the city center, the main urban areas stretch along the coasts of lake Zurich, north-west along the Limmattal, north towards Oerlikon and Zurich airport, as well as north-east including the neighboring city of Duebendorf. In between those urban areas, the area has suburban to rural character including several mountains and agricultural land-use. The network has a total length of 2'646km and consists of approx. 23'600 edges and 18'900 nodes. The network is filtered such that it only includes cycling-relevant edges, i.e. highways are excluded through the OSM highway tags `motorway`, `motorway_link`, `trunk`, `trunk_link`. The network is enriched with cycling-relevant choice attributes, as shown in Table 4.2 (note that some attributes do not have a full network coverage, resulting in sectional probabilities not adding to 100%).

The cycling infrastructure is derived from the relevant OSM tags. Bike paths are physically separated from the motorized infrastructure. There are a total of 24.4km of bicycle paths, most of which are located in the city center. Bike lane consist of painted marking / lanes on motorized streets. They are not physically separated from motorized traffic. There is a total 178.4km of bike lanes, distributed throughout most of the densely built urban areas. Mixed bike paths are any paths or tracks that are suitable for cyclists and pedestrians simultaneously. There is a total of 477.8km mixed bike paths, mostly located in the sub-urban and rural areas. These e.g. include the paths across all forests, and make up a substantial share of the total network. The speed limit information is sourced from OSM, with most streets having a 50kph limit. Information about gradients is derived from the Google Elevation API. The number of motorized (one-directional) lanes is derived from OSM tags and the network simplification protocol. Traffic levels are derived from the NPVM (ARE, 2017) and represented through annual average daily traffic (AADT) counts. Note that the traffic counts are not available for all of the network that is accessible for motorized traffic, as the OSM network is more detailed than the one used in the NVPM. Information about traffic signals for motorized transport (i.e. excluding cycling-related signalization) is derived from the OSM `highway` tag for nodes.

Figure 4.1: Zurich network with bicycle paths marked in green, mixed paths in blue and bicycle lanes in orange.



Descriptive results The descriptive route choice behavior is shown in Table 4.2. Apart from the network composition, it shows the shares of choice-relevant attributes for the chosen, i.e. observed routes, and their shortest route equivalents, as well as for the generated choice set. For the area of interest, the raw data includes around 52'000 trajectories validated as either bike or E-bike (the latter through manual user input). These trajectories are initially filtered for inplausible speeds and/or distances, as well as for noisy waypoints (single GPS measurement). The map matching is done through a commonly applied Hidden-Markov-Model based on Newson and Krumm (2009). After matching, unsuccessful matches, e.g. through too noisy GPS measurements, are filtered using different classification metrics (see Meister et al. (2021) for details on the complete matching pipeline). Finally, trajectories with a detour-factor of more than 3 are filtered, as this generates problems with the shortest-path based choice set generation algorithms applied later on. The final sample consists of 36'630 trajectories, for each of which a choice set is generated using the MH algorithm. We run 10'000 iterations for each OD pair, resulting in an average choice set size of 25.4.

Table 4.2: Descriptive statistics of the network for Zurich.

	Network	Shortest	Chosen	Choice set
Observations [n]	-	36'630	36'630	932'084
Length [km]	2'646.16	1.84	4.44	5.17
Bike path [km]	0.9%	4.3%	3.6%	2.7%
Bike path mixed [km]	18.0%	10.8%	13.2%	10.4%
Bike lane [km]	6.7%	27.7%	28.6%	20.3%
Speedlimit $\leq$ 30kph [km]	26.1%	31.1%	33.2%	40.0%
Speedlimit 31-50kph [km]	63.5%	62.0%	58.7%	55.9%
Speedlimit >50kph [km]	6.4%	4.4%	3.5%	2.0%
Slope <2% [km]	78.0%	83.6%	84.5%	82.7%
Slope 2-6% [km]	14.5%	11.9%	11.9%	12.1%
Slope 6-10% [km]	5.3%	3.2%	3.1%	3.6%
Slope >10% [km]	2.2%	1.3%	0.5%	1.6%
Traffic <5k AADT [km]	70.2%	44.5%	45.2%	56.8%
Traffic 5k-15k AADT [km]	4.0%	10.8%	8.1%	7.9%
Traffic >15k AADT [km]	0.1%	1.6%	0.6%	0.7%
N lanes = 1 [km]	58.7%	28.2%	30.6%	41.4%
N lanes = 2 [km]	22.3%	14.1%	13.2%	14.1%
N lanes = 3 [km]	2.7%	3.8%	2.4%	2.9%
N lanes $\geq$ 4 [km]	3.2%	10.3%	7.4%	7.1%
Traffic signals [n]	500	6.81	8.12	7.95

Note: Only the gradient attribute has full network coverage and the probabilities correspondingly add to 100%.

Comparing the chosen routes with their shortest-path equivalents allows one to gain first insights into the choice behavior. The first notable difference is the average distance, which is more than twice that of the average shortest distance. This difference is an important indicator for the complexity of the underlying choice processes which, when, e.g. compared to car route choices, are influenced by much more factors than just distance/time. Comparable studies (Meister et al., 2021, 2023) report values of around 150%. It can be assumed that the even higher difference in the data at hand is partly due to the simplified network.

Generally, the patterns between the shares of attributes in the shortest and chosen routes reveal mostly anticipated preferences. Favorable attributes, such as cycling infrastructure, have a slightly higher share in the observed routes. This is surprisingly not true for cycling paths which cyclists typically have the highest preference for when compared to other infrastructure types (see also Chapter 5.2 on the stated preference experiment). This can potentially be explained by the fact that for Zurich, the few existing cycle paths are located along the main corridors that traverse the city center, hence the higher share in the shortest routes. Simultaneously, these corridors must have other, negatively perceived, attributes (e.g. motorized traffic) that result in cyclists to make a detour.

Other favorable attributes such as speed limits of 30kph, low traffic volumes or streets with only one motorized lane have higher shares in the observed routes. Unfavorable attributes, such as higher speed limits, higher traffic volumes, or higher number of motorized lanes, intuitively have smaller shares in the observed routes. They also consistently have smaller shares across all gradient levels larger than 2%. The average number of traffic signals along a path is higher for the chosen routes. The behavioral interpretation of traffic signals is ambiguous and it is not clear whether this represents a positive or negative attribute. This was already shown in previous work using the same study area and a similar network (Meister et al., 2023). From a negative perspective, traffic signals do to some extent serve as proxies for large complex intersections, which are objectively unfavorable. However, they could also have some (random appearing) spatial correlation with another positively perceived attribute.

Estimation results The model estimation results are shown in Table 4.3. We estimated two separate PSLs based on the utility function 4.3, one containing only base parameters (see Table 4.2), the other additionally containing interaction effects onto the base parameters. The interaction effects are included as binary dummy variables and cover the three available type of bikes (regular bicycle, E-bike, S-pedelec), the gender and the age. The latter is binary encoded into older/younger than 40 years.

For the simple model, all parameters have to be considered in relation to the reference alternative. The reference alternative constitutes of a street with two motorized lanes, without cycling infrastructure, a speed limit of 50kph, a gradient smaller than 2%, and traffic volumes of less than 5k AADT. The parameters all show the expected signs. The length parameter is negative and significant which is a commonly used indicator for the behavioral validity of route choice models (i.e. utilitarian cyclists prefer a shorter over a longer route). The estimates for the cycling infrastructure parameters align with the insights drawn from the descriptive analysis. The bike path parameter is positive, but the smallest compared to the others. It is further not (even close to being) significant. This is counter-intuitive and not aligned with the related literature. As mentioned previously, this is probably related to (a) the sparse availability of bike paths in Zurich, and (b) underlying multicolinearity with other choice-relevant attributes. The mixed bike path parameter is significant and has the highest estimate compared to the other infrastructure types. This is most probably due to the high share of such paths in the network. Considering the technical definition of such paths in this network, the literature usually reports pedestrian interactions on urban paths to be negatively perceived. The bike lane parameter is positive and significant. It is the main type of cycling infrastructure in the urban parts of the considered area, hence also the higher estimate compared to regular bike paths.

The estimates for the speed limits have the expected signs and are both significant. Compared to the reference street with a 50kph speed limit, streets with a slower speed limit of 30kph are positively perceived, those with higher limits, typically main arterial roads for motorized traffic with a limit of 70kph (highways are excluded from the network), are perceived

Table 4.3: Estimation results for the Zurich models.

	PSL_1		PSL_2	
	est.	std.	est.	std.
Length	-0.96***	-8.01	-0.89***	-7.98
Bike path	0.12	0.41	0.55*	1.66
S-pedelec			-0.16	-1.51
E-bike			-0.09	-1.44
Male			-0.16	-1.55
Bike path mixed	0.66***	5.36	0.69***	3.67
S-pedelec			-0.45**	-2.27
E-bike			-0.38	-1.62
Older $\geq$ 40			0.13	1.59
Bike lane	0.48***	3.93	0.43***	2.64
E-bike			0.13	1.50
S-pedelec			0.21	1.47
Older $\geq$ 40			-0.11	-1.42
Male			0.03	1.63
Speedlimit $\leq$30kph	0.27***	3.42	0.32***	2.90
S-pedelec			-0.07	-1.42
Speedlimit >50kph	-0.34*	-1.67	-0.47*	-1.64
E-bike			0.18	1.62
S-pedelec			0.14	1.32
Male			0.41**	1.96
Slope 2-6%	-0.39***	-2.69	-0.48**	-2.25
S-pedelec			0.51*	1.73
Slope 6-10%	-2.15***	-6.92	-2.81***	-5.42
E-bike			0.41	1.57
S-pedelec			1.47**	2.11
Slope >10%	-7.09***	-9.36	-8.09***	-6.70
S-pedelec			1.41	1.60
Traffic 5-15k AADT	-0.22*	-1.67	-0.54**	-2.03
Traffic $\geq$ 15k AADT	-1.48***	-4.27	-0.76*	-1.78
Older $\geq$ 40			-0.71	-1.47
Male			-0.22	-1.40
N lanes = 1	-0.36***	-2.80	-0.36***	-3.02
N lanes = 3	-1.31***	-3.90	-1.34***	-4.47
N lanes $\geq$ 4	-0.16*	-1.65	-0.23*	-1.68
Traffic signals	0.05***	5.37	0.06***	2.99
S-pedelec			0.14*	1.78
PS	3.30***	66.02	3.29***	65.90
Parameters	16		72	
Final LL	-46’978.18		-46’674.86	
AIC	93’988.01		93’492.72	
BIC	94’124.13		94’104.82	
Rho2	0.55		0.56	

Note: ***p<0.01, **p<0.05, *p<0.1 using robust standard errors.

negatively. The estimates for the different gradients show the expected sign and are all significant. The relative spread between the estimates is aligned with the results from previous studies for Zurich (Meister et al., 2023) and reflect the distinct topological conditions of Zurich compared to other e.g. European cities. The estimates for traffic volumes are significant and have the expected signs. Both are negative and the effect grows proportionally to the traffic volume.

The estimates for the number of motorized lanes are not as fully intuitive. Compared to the reference street with two motorized lanes (independent of directions), the parameter for having only one motorized lane (i.e. a one-way street) is negative and significant. The parameter for having three motorized lanes is negative and significant which is expected. Further increasing the number of lanes to four or more, also results in a negative and significant parameter, however, with a smaller effect than for three lanes. This is aligned with the comparably high share of such streets seen in the descriptive analysis, and most probably due to the fact, that these are located at bottlenecks, most notably bridges, which cannot easily be detoured by cyclists (e.g. Hardturmbruecke, Quaibruecke). The estimate for traffic signals is positive and significant. As previously mentioned, it is unclear how to interpret this attribute. While traffic signals are generally found at larger intersections, some of the most complex intersection (e.g. Central near the main station) don't have any. Just like with the parameters for motorized lanes, it could be that signaled intersections are located at central corridors or bottlenecks in the network, making them unfeasible for detouring. Finally, the parameter for the PS metric is positive and highly significant. This is according to theory and indicates a substantial amount of overlap within the choice sets.

The second model includes interaction effects for socio-demographics and the type of bikes, totaling in 72 model parameters (as opposed to 16 in the first one). The reference level for these parameters are female respondents under 40 years of age with a regular bike. We only show the interaction parameters that are (close to being) significant at the 10% level. The fit-of-model indicators listed at the bottom of Table 4.3 show a slight increase in model fit. The base parameters mostly show the same patterns w.r.t. estimate sign and significance as for first model. The only notable difference relates to the bike path parameter, with it's estimate turning out larger than the one for bike lanes and being slightly significant. This is clearly more intuitive than in the first model, however, it must be noted that the interaction effects for the bike path parameter are all negative, reducing the effect on utility for E-bikes, S-pedelecs and males in general. The interaction effects for the type of bike across the different types of cycling infrastructure are intuitive and generally aligned with the literature, where electric bikes and S-pedelecs tend to be less prone to mixing with motorized traffic due to their higher speeds. The same holds for males, which are known to be less averse to risk, in this case related to mixing with motorized traffic.

These just mentioned insights are also reflected in the interactions on speed limits, where S-pedelecs have a reduced positive utility of 30kph speed limits, but S-pedelecs, E-bikes and males in general, have a less negative utility of higher speed limits. The notable interaction effects for the different gradient levels are related to the type of bike used. As expected and shown in previous work Meister et al. (2023), electric bikes, especially S-pedelecs, reduce the negative perception of gradients. The strongest interaction is found for S-pedelecs and gradients between 6-10%. For the different levels of traffic volumes, no interaction effect could be found related to the type of bike. One would generally assume a reduced negative utility, due to the previously mentioned higher speeds of electric bikes. It should however be noted, that AADT values around 10k already represent considerable amounts of traffic and only constitute a tiny fraction of network. The only notable interaction effects relate to males and cyclists older than 40 years, both being negative. This is counter-intuitive and probably due to the skewed sample composition and/or unbalanced number of observation per respondent.

For the number of motorized lanes, no noticeable interaction effects are found. As with the traffic volumes, one would assume effects related to the inherent risk of mixing with traffic. However, one has to consider that the number of motorized lanes, traffic volumes and speeds, as well as separation of traffic through cycling infrastructure, all correlate with respect to riding safety, making it challenging for the model to properly disentangle and isolate all individual effects. Finally, there is a significant positive effect of S-pedelecs on traffic signals. Just like with the base parameter itself, it is unclear how to behaviorally interpret this.

4.1.2 Basel

Sample composition The sample consists of individuals that provided user-validated cycling trips (validation of detected trips through the Catch-my-Day app was not required but encouraged, see Chapter 3.3) that could be successfully processed for the respective modeling approach (i.e. mostly related to map matching). The differentiation between different bike types is based on the initial questionnaire, where respondents had to state which bike type they use the most. The Catch-my-Day app cannot automatically detect differences between regular, E-bikes and S-pedelecs. Table 4.4 presents the socio-demographics attributes of the complete sample, the bike-specific sub-samples, and the census (MTMC) reference (BFS, 2023).

Table 4.4: Socio-demographic attributes of the Basel sample with MTMC reference.

Attribute		Bike (n = 280)	E-bike (n = 105)	S-pedelec (n = 168)	Total (n = 553)	MTMC
Gender	Male	0.61	0.41	0.65	0.59	0.49
	Female	0.39	0.59	0.35	0.31	0.51
Age	< 40	0.45	0.21	0.19	0.32	0.41
	40 - 60	0.43	0.49	0.57	0.48	0.33
	> 60	0.07	0.30	0.24	0.20	0.26
Income	NA	0.04	0.05	0.02	0.04	0.21
	Low (< 4kCHF)	0.12	0.07	0.02	0.03	0.09
	Mid (4-12kCHF)	0.54	0.56	0.58	0.55	0.58
	High (> 12kCHF)	0.30	0.32	0.38	0.38	0.12
Education	Mandatory	0.03	0.01	0.02	0.01	0.23
	Secondary	0.34	0.52	0.49	0.56	0.49
	Higher	0.63	0.47	0.49	0.43	0.28

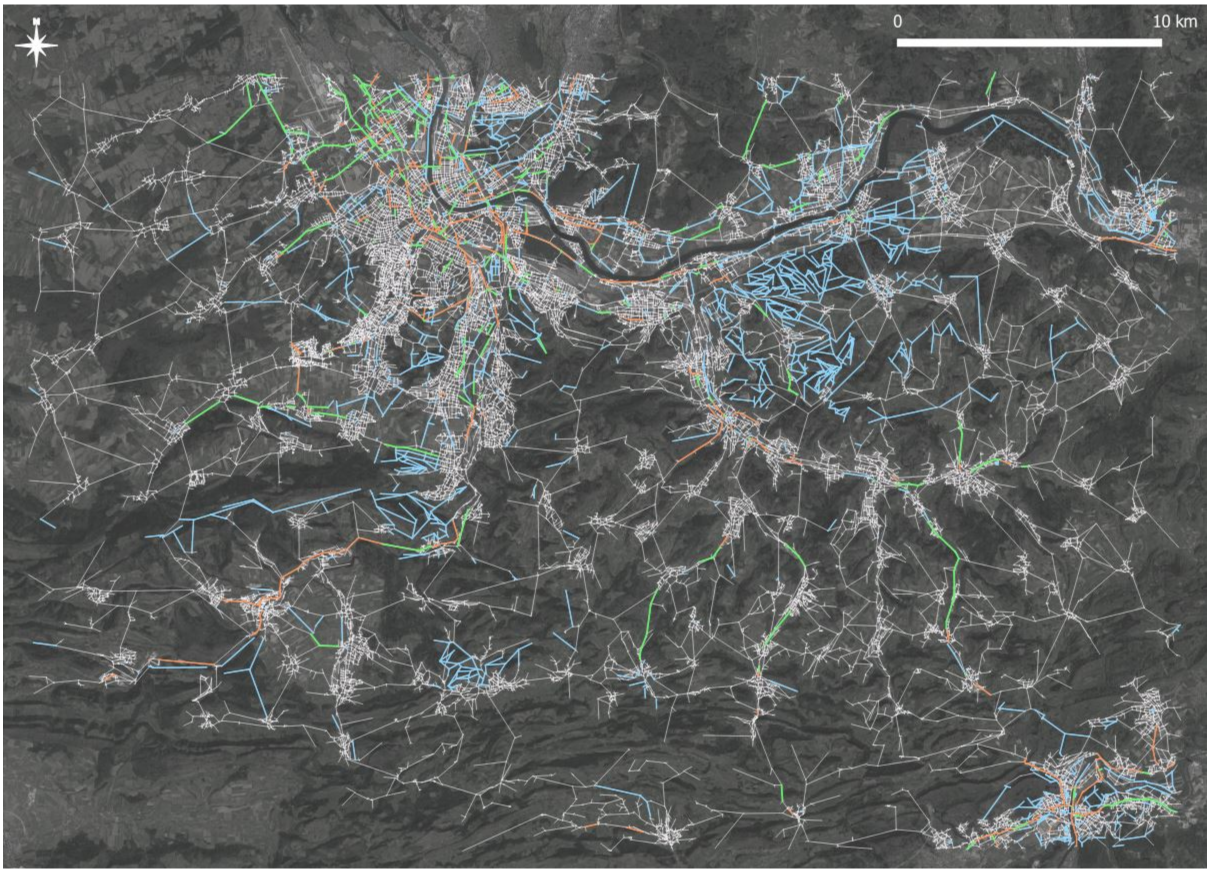
The complete sample consists of 553 individuals, with non-regular bike users comprising about 50%. It can be seen that, compared to the census reference, the sample is biased towards being rather male, slightly older, better educated and with higher income. Considering the sub-samples, one can see that the S-pedelec users are even stronger biased towards being male, older, and even higher income. This bias gets smaller when considering the E-bikes, and even smaller for regular bikes. The patterns across the different sub-samples are aligned with the general literature on types of cyclists and bike-ownership. As shown in previous Swiss studies (Molloy et al., 2022), cyclists are typically better educated, whereas this overlaps with the general education bias of academic GPS-tracking studies. E-bikes and especially S-pedelecs usually represent a substantial monetary investment and are typically more accessible to higher income and older cohorts.

Network The network is generated using the SNMAN package (Ballo and Axhausen, 2023). The package uses an Open-Street-Map (OSM) network as basis and then simplifies it by merging parallel edges to center-lines (i.e. one edge for a multi-modal street section) and consolidating intersections. The simplification is crucial to avoid ambiguities when matching noisy GPS traces to the network. Furthermore, the simplification reduces the network complexity, which in turn substantially reduces the time required to process the comparably large amounts of data collected in this study. The resulting network is shown in Figure 4.2.

The network covers an area of approx. 1,270km^2 and includes both the canton of Basel Stadt and Basel Land. The main urban areas include the whole city of Basel, smaller cities like Muttenz and Rheinfelden east-wards along the Rhine, cities like Aesch south of Basel, as well as parts of the city of Olten (technically part of canton Solothurn) in the south-east. Apart from these, the network covers multiple smaller satellite cities with comparably low building density as well as rural areas characterized by rolling-hills and agricultural land-use. The network has a total length of 5'682km and consists of approx. 42'600 edges and 34'300 nodes. The network is filtered such that it only includes cycling-relevant edges, i.e. highways are excluded through the OSM highway tags `motorway`, `motorway_link`, `trunk`, `trunk_link`. The network is enriched with cycling-relevant choice attributes, as shown in Table 4.2 (note that some attributes do not have a full network coverage, resulting in sectional probabilities not adding to 100%).

The cycling infrastructure is derived from the relevant OSM tags. Bike paths are physically separated from the motorized infrastructure. There is a total of 106.1km of bike paths, with the majority located in the core urban area of Basel city, occasionally stretching out into the sub-urban catchment areas. Bike lane consist of painted marking / lanes on motorized streets. They are not physically separated from motorized traffic. There is a total of 122.8km of bike lanes, which are predominately located in the dense urban centers of Basel (and Olten). Mixed bike paths are any paths or tracks that are suitable for cyclists and pedestrians simultaneously. There is a total of 664.5km of mixed bike paths, mostly located outside the cities in rural areas (these e.g. include the paths across all forests). The speed limit information is sourced from OSM, with most streets having a 50kph limit. Information about gradients is derived from the Google Elevation API. The number of motorized (one-directional) lanes is derived from OSM tags and the network simplification protocol. Traffic levels are derived from the NPVM (ARE, 2017) and represented through annual average daily traffic (AADT) counts. Note that the traffic counts are not available for all of the network that is accessible for motorized traffic, as the OSM network is more detailed than the one used in the NVPM. Information about traffic signals for motorized transport (i.e. excluding cycling-related signalization) is derived from the OSM `highway` tag for nodes.

Figure 4.2: Basel network. Bike paths are marked in green, mixed bike paths in blue, and bike lanes in orange.



Descriptive results The descriptive route choice behavior is shown in Table 4.5. Apart from the network composition, it shows the shares of choice-relevant attributes for the chosen, i.e. observed routes, and their shortest route equivalents, as well as for the generated choice set. For the area of interest, the raw data includes around 56’000 trajectories validated as either bike or E-bike (the latter through manual user input). These trajectories are initially filtered for inplausible speeds and/or distances, as well as for noisy waypoints (single GPS measurement). The map matching is done through a commonly applied Hidden-Markov-Model based on Newson and Krumm (2009). After matching, unsuccessful matches, e.g. through too noisy GPS measurements, are filtered using different classification metrics (see Meister et al. (2021) for details on the complete matching pipeline). Finally, trajectories with a detour-factor of more than 3 are filtered, as this generates problems with the shortest-path based choice set generation algorithms applied later on. The final sample consists of 39’999 trajectories, for each of which a choice set is generated using the MH algorithm. We run 10’000 iterations for each OD pair, resulting in an average choice set size of 27.1.

Table 4.5: Descriptive statistics of the network for Basel.

	Network	Shortest	Chosen	Choice set
Observations [n]	-	39'999	39'999	1.086,651
Length [km]	5'682.34	1.76	4.12	4.90
Bike path [km]	1.8%	4.3%	7.1%	4.2%
Bike path mixed [km]	11.6%	10.8%	8.2%	5.9%
Bike lane [km]	2.1%	27.7%	15.8%	11.1%
Speedlimit $\leq$ 30kph [km]	10.9%	32.6%	27.2%	31.9%
Speedlimit 31-50kph [km]	82.4%	60.8%	65.9%	61.4%
Speedlimit >50kph [km]	5.8%	5.4%	4.4%	3.5%
Slope <2% [km]	73.4%	83.6%	91.2%	89.6%
Slope 2-6% [km]	14.9%	11.9%	7.5%	8.1%
Slope 6-10% [km]	8.0%	3.2%	0.9%	1.8%
Slope >10% [km]	3.5%	0.1%	0.5%	0.5%
Traffic <5k AADT [km]	82.8%	44.5%	59.8%	69.7%
Traffic 5k-15k AADT [km]	1.9%	10.8%	8.1%	8.0%
Traffic >15k AADT [km]	0.1%	1.6%	0.5%	0.1%
N lanes = 1 [km]	68.1%	28.2%	41.0%	50.9%
N lanes = 2 [km]	19.0%	14.1%	23.2%	23.0%
N lanes = 3 [km]	0.1%	3.8%	2.9%	2.8%
N lanes $\geq$ 4 [km]	0.1%	10.3%	0.1%	1.8%
Traffic signals [n]	210	6.81	2.45	2.51

Note: Only the gradient attribute has full network coverage and the probabilities correspondingly add to 100%.

Comparing the chosen routes with their shortest-path equivalents allows one to gain first insights into the choice behavior. The first notable difference is the average distance, which is more than twice that of the average shortest distance. This difference is an important indicator for the complexity of the underlying choice processes which, when, e.g. compared to car route choices, are influenced by much more factors than just distance/time. Comparable studies (Meister et al., 2021, 2023) report values of around 150%. It can be assumed that the even higher difference in the data at hand is partly due to the simplified network.

Generally, the patterns between the shares of attributes in the shortest and chosen routes reveal mostly anticipated preferences. Considering the cycling infrastructure, the share of bike paths along the chosen routes is almost twice as high as those for the shortest routes. This is expected, as infrastructure that is physically separated from motorized traffic is generally favored by cyclists (see also Chapter 5.2 on the stated preference experiment). Both other types of cycling infrastructure have lower shares in the chosen routes. While bike lanes are known to be less favorable due to their exposure to motorized traffic, the pattern w.r.t. mixed bike paths could potentially be explained by their spatial distribution within the network, as well as the fact that pedestrians are using those as well.

Looking at the speed limits, one can see that the shares for speed limits above 50kph are lower in the chosen routes. However, this is also true for both lower speed limit levels, potentially indicating that cyclist don't care too much about increasing shares on low speed streets, but clearly do try to avoid streets with speeds higher than 50kph. The gradient levels show lower shares in the chosen routes for anything greater than 2%, except for segments greater than 10%. The latter seems counter intuitive and can potentially be linked to the spatial distribution of such links, e.g. at bottlenecks in the network, as well as the usage of electric bikes. Other unfavorable attributes such as traffic volumes over 5k AADT, and (inherently correlated) streets with more than two motorized lanes show lower shares in the chosen routes. The large difference w.r.t street with four or more motorized lanes is a good indicator that these are present at bottleneck locations such as bridges. Finally, the number of traffic signals along the chosen routes is more than half as for the shortest routes. This is intuitive, considering that traffic signals serve as proxy for large, complex intersections.

Estimation results The model estimation results are shown in Table 4.6. We estimated two separate PSLs based on the utility function 4.3, one containing only base parameters (see Table 4.5), the other additionally containing interaction effects onto the base parameters. The interaction effects are included as binary dummy variables and cover the three available type of bikes (regular bike, E-bike, S-pedelec), the gender and the age. The latter is binary encoded into older/younger than 40 years.

For the simple model, all parameters have to be considered in relation to the reference alternative. The reference alternative constitutes of a street with two motorized lanes, without cycling infrastructure, a speed limit of 50kph, a gradient smaller than 2%, and traffic volumes of less than 5k AADT. The parameters mostly show the expected signs. The length parameter is negative and significant which is a commonly used indicator for the behavioral validity of route choice models (i.e. utilitarian cyclists prefer a shorter over a longer route). The estimates for the cycling infrastructure parameters align with the insights drawn from the descriptive analysis. The bike path parameter is positive, significant, and the largest compared to the others. The mixed bike path parameter is significant and has the second highest cycling infrastructure estimate. This is most probably due to the substantial amount of such paths in the network. Considering the technical definition of such paths in this network, i.e. paths available to cyclists and pedestrians, the literature usually reports pedestrian interactions on urban paths to be negatively perceived. The bike lane parameter is positive and significant, but has the lowest estimate.

The estimates for the speed limits have the expected signs and are both significant. Compared to the reference street with a 50kph speed limit, streets with a slower speed limit of 30kph are positively perceived. This is a finding that was not suggested by the previous descriptive analysis and highlights the necessity of modeling the data to generate behavioral insights. Streets with higher limits, typically main arterial roads for motorized traffic with a limit of 70kph (highways are excluded from the network), are perceived negatively. The estimates for the different gradients show the expected signs and are all significant. The relative spread between the estimates is aligned with the results from previous studies for Switzerland (Meister et al., 2023) and reflect the distinct topological conditions compared to other e.g. European cities. The estimates for traffic volumes are significant and have the expected signs. Both are negative and the effect grows with to the traffic volume.

The estimates for the number of motorized lanes are also intuitive and as expected. Compared to the reference street with two motorized lanes (independent of directions), the param-

Table 4.6: Estimation results for the Basel models.

	PSL_1		PSL_2	
	est.	std.	est.	std.
Length	-1.50***	-11.75	-1.48***	-11.63
Bike path	1.60***	8.41	1.13***	3.85
S-pedelec			0.46**	2.16
E-bike			0.17	1.48
Older $\geq$ 40			0.55	1.49
Bike path mixed	0.94***	5.46	0.92***	3.41
Older $\geq$ 40			0.54***	2.64
Bike lane	0.55***	4.22	0.55***	2.55
Older $\geq$ 40			-0.26	-1.53
Speedlimit $\leq$ 30kph	0.18**	2.03	0.05*	1.68
E-bike			0.41***	2.02
Speedlimit >50kph	-0.51***	-3.80	-0.24*	-1.75
Slope 2-6%	-1.02***	-3.78	-1.98**	-4.34
E-bike			1.00	1.42
Slope 6-10%	-4.14***	-9.38	-5.20***	-5.29
E-bike			1.81*	1.66
Slope >10%	-6.61***	-5.47	-10.32***	-4.61
E-bike			4.71*	1.67
Traffic 5-15k AADT	-0.11	-0.52	0.64***	2.50
Male			-0.39***	-2.57
Traffic $\geq$ 15k AADT	-3.15***	-6.88	-2.14***	-2.54
Male			-1.78**	-2.26
N lanes = 1	0.15	1.17	0.32*	1.87
N lanes = 3	-0.23	-0.78	-0.85**	-2.05
S-pedelec			0.83*	1.88
N lanes $\geq$ 4	-0.92***	-2.70	-1.68***	-2.51
S-pedelec			1.51***	2.49
Traffic signals	0.14***	6.47	0.14***	3.30
PS	3.20***	54.13	3.13***	49.48
Parameters	16		72	
Final LL	-53'776.83		-53'457.76	
AIC	107'584.22		107'058.38	
BIC	107'573.19		106'935.57	
Rho2	0.52		0.53	

Note: ***p<0.01, **p<0.05, *p<0.1 using robust standard errors.

eter for having only one motorized lane (i.e. a one-way street) is positive and significant. The parameters for having three motorized lanes is negative and significant, and grow even more negative when increasing to four or more lanes. The estimate for traffic signals is positive and significant. This is counter intuitive and, just like with 30kph speed limits, not what the descriptive analysis suggests. The reasons for that are unclear and probably related to multicolinearity in the data. Finally, the parameter for the PS metric is positive and highly significant. This is according to theory and indicates a substantial amount of overlap within the choice sets.

The second model includes interaction effects for socio-demographics and the type of bikes, totaling in 72 model parameters (as opposed to 16 in the first one). The reference level for these parameters are female respondents under 40 years of age with a regular bike. We only show the interaction parameters that are (close to being) significant at the 10% level. The fit-of-model indicators listed at the bottom of Table 4.6 show a slight increase in model fit. The base parameters mostly show the same patterns w.r.t. estimate sign and significance as for first model. For the cycling infrastructure, the interactions for older respondents are intuitive. Elder cyclists can assumed to be more risk averse generally, and specifically w.r.t. mixing with motorized traffic. This is clearly reflected in the positive effect on (mixed) bike paths and the negative one on bike lanes. The interactions of S-pedelecs and E-bikes on bike paths are not as expected, as the higher speeds of these bikes typically favor riding on actual streets, i.e. bike lanes. Similarly, the positive interaction of E-bikes onto low speed limits is counter intuitive and opposes findings from previous, comparable studies (Meister et al., 2023). Both these patterns are probably related to sample bias, unbalanced number of observation per respondent, and/or multicolinearity within the data.

The interaction effects for the different gradient levels are solely related to E-bikes (interestingly, no notable S-pedelec interactions are found). The E-bikes reduce the negative perception of gradients and this compensation effect grows proportionally to the gradient. For the traffic volume levels, two negative interaction effects of being male are found. Both are not intuitive as one generally expect the less risk averse males to be more comfortable around higher traffic volumes when compared to females. Finally, two positive interaction effects related to using S-pedelecs on streets with three or more motorized lanes are found. While both these seem reasonable due to the considerably higher speeds of S-pedelecs, both interactions almost completely compensates the negative utility contribution of such a road layout which seems slightly overestimated.

4.1.3 Aarau

Sample composition The sample consists of individuals that provided user-validated cycling trips (validation of detected trips through the Catch-my-Day app was not required but encouraged, see Chapter 3.3) that could be successfully processed for the respective modeling approach (i.e. mostly related to map matching). The differentiation between different bike types is based on the initial questionnaire, where respondents had to state which bike type they use the most. The Catch-my-Day app cannot automatically detect differences between regular, E-bikes and S-pedelecs. Table 4.7 presents the socio-demographics attributes of the complete sample, the bike-specific sub-samples, and the census (MTMC) reference (BFS, 2023).

Table 4.7: Socio-demographic attributes of the Aarau sample with MTMC reference.

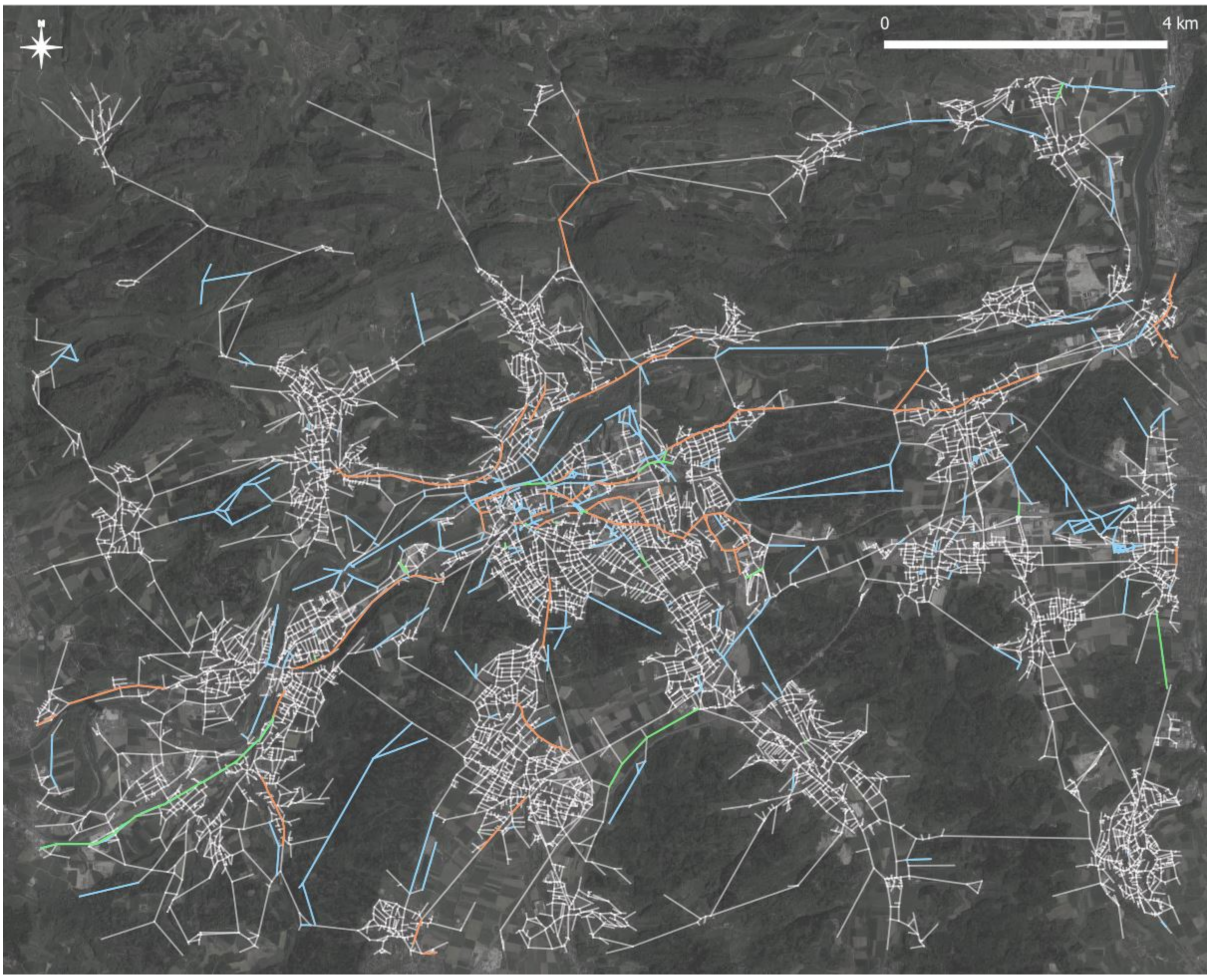
Attribute		Bike (n = 48)	E-bike (n = 36)	S-pedelec (n = 32)	Total (n = 116)	MTMC
Gender	Male	0.52	0.44	0.81	0.57	0.49
	Female	0.48	0.56	0.19	0.43	0.51
Age	< 40	0.5	0.29	0.27	0.34	0.41
	40 - 60	0.45	0.58	0.50	0.50	0.33
	> 60	0.05	0.15	0.23	0.16	0.26
Income	NA	0.04	0.02	0.06	0.04	0.21
	Low (< 4kCHF)	0.02	0.00	0.03	0.02	0.09
	Mid (4-12kCHF)	0.58	0.55	0.46	0.54	0.58
	High (> 12kCHF)	0.36	0.43	0.45	0.40	0.12
Education	Mandatory	0.02	0.02	0.00	0.02	0.23
	Secondary	0.19	0.57	0.54	0.40	0.49
	Higher	0.79	0.41	0.46	0.58	0.28

The complete sample consists of 116 individuals, with non-regular bike users comrpising about 60%. It can be seen that, compared to the census reference, the sample is biased towards being rather male, slightly older, better educated, and with higher income. Considering the sub-samples and keeping the comparably small sample sizes in mind, one can see that the E-bike and S-pedelec users are even stronger biased towards being male, older, and higher income. The sub-sample of regular bike users, shows the same patterns, with a notable difference of being substantially younger. The patterns across the different sub-samples are aligned with the general literature on types of cyclists and bike-ownership. As shown in previous Swiss studies (Molloy et al., 2022), cyclists are typically better educated, whereas this overlaps with the general education bias of academic GPS-tracking studies. E-bikes and especially S-pedelecs usually represent a substantial monetary investment and are typically more accessible to higher income and older cohorts.

Network The network is generated using the SNMAN package (Ballo and Axhausen, 2023). The package uses an Open-Street-Map (OSM) network as basis and then simplifies it by merging parallel edges to center-lines (i.e. one edge for a multi-modal street section) and consolidating intersections. The simplification is crucial to avoid ambiguities when matching noisy GPS traces to the network. Furthermore, the simplification reduces the network complexity, which in turn substantially reduces the time required to process the comparably large amounts of data collected in this study. The resulting network is shown in Figure 4.3.

The network covers an area of approx. 197km^2 and includes the whole municipality of the city of Aarau. The main urban areas include the city of Aarau, smaller neighboring cities like Niedergoesgen, Unterentfelden and Suhr to the south, and Hunzenschwil to the southeast. The area in between these main cities can be characterized as rural. The network has a total length of 1’110km and consists of approx. 10’700 edges and 9’000 nodes. The network is filtered such that it only includes cycling-relevant edges, i.e. highways are excluded through the OSM highway tags [`motorway`, `motorway_link`, `trunk`, `trunk_link`]. The network is enriched

Figure 4.3: Aarau network. Bike paths are marked in green, mixed bike paths in blue, and bike lanes in orange.



with cycling-relevant choice attributes, as shown in Table 4.8 (note that some attributes do not have a full network coverage, resulting in sectional probabilities not adding to 100%).

The cycling infrastructure is derived from the relevant OSM tags. Bike paths are physically separated from the motorized infrastructure. There is a total of 9.3km of bike paths, mostly located outside the main city of Aarau, serving as connectors between neighboring cities. Bike lane consist of painted marking / lanes on motorized streets. They are not physically separated from motorized traffic. There is a total of 32.9km of bike lanes, predominately located in the center of Aarau, occasionally stretching out into the catchment area / neighboring cities. Mixed bike paths are any paths or tracks that are suitable for cyclists and pedestrians simultaneously. There is a total of 93.9km of mixed bike paths, somewhat evenly distributed in the center of Aarau, as well as connecting into neighboring cities or surrounding rural areas. The speed limit information is sourced from OSM, with most streets having a 50kph limit. Information about gradients is derived from the Google Elevation API. The number of motorized (one-directional) lanes is derived from OSM tags and the network simplification protocol. Traffic levels are derived from the NPVM (ARE, 2017) and represented through annual average daily traffic (AADT) counts. Note that the traffic counts are not available for all of the network that is accessible for motorized traffic, as the OSM network is more detailed than the one used in the NVPM. Information about traffic signals for motorized transport (i.e. excluding cycling-related signalization) is derived from the OSM `highway` tag for nodes.

Descriptive results The descriptive route choice behavior is shown in Table 4.8. Apart from the network composition, it shows the shares of choice-relevant attributes for the chosen, i.e. observed routes, and their shortest route equivalents, as well as for the generated choice set. For the area of interest, the raw data includes around 6'800 trajectories validated as either bike or E-bike (the latter through manual user input). These trajectories are initially filtered for inplausible speeds and/or distances, as well as for noisy waypoints (single GPS measurement). The map matching is done through a commonly applied Hidden-Markov-Model based on Newson and Krumm (2009). After matching, unsuccessful matches, e.g. through too noisy GPS measurements, are filtered using different classification metrics (see Meister et al. (2021) for details on the complete matching pipeline). Finally, trajectories with a detour-factor of more than 3 are filtered, as this generates problems with the shortest-path based choice set generation algorithms applied later on. The final sample consists of 3'799 trajectories, for each of which a choice set is generated using the MH algorithm. We run 10'000 iterations for each OD pair, resulting in an average choice set size of 29.9.

Comparing the chosen routes with their shortest-path equivalents allows one to gain first insights into the choice behavior. The first notable difference is the average distance, which is more than twice that of the average shortest distance. This difference is an important indicator for the complexity of the underlying choice processes, which when, e.g. compared to car route choices, are influenced by much more factors than just distance/time. Comparable studies (Meister et al., 2021, 2023) report values of around 150%. It can be assumed that the even higher difference in the data at hand is partly due to the simplified network.

Table 4.8: Descriptive statistics of the network for Aarau

	Network	Shortest	Chosen	Choice set
Observations [n]	-	3’799	3’799	113’902
Length [km]	1’110.97	1.19	2.92	3.44
Bike path [km]	0.8%	0.1%	0.1%	0.1%
Bike path mixed [km]	8.4%	10.1%	10.6%	11.6%
Bike lane [km]	2.9%	21.9%	15.8%	11.5%
Speedlimit $\leq$ 30kph [km]	15.4%	30.3%	35.5%	36.7%
Speedlimit 31-50kph [km]	75.2%	62.4%	57.9%	56.8%
Speedlimit >50kph [km]	9.0%	4.8%	2.8%	3.1%
Slope <2% [km]	80.5%	83.7%	85.9%	86.2%
Slope 2-6% [km]	12.7%	14.3%	12.1%	11.3%
Slope 6-10% [km]	4.5%	1.9%	1.8%	2.3%
Slope >10% [km]	2.2%	0.1%	0.1%	0.1%
Traffic <5k AADT [km]	94.6%	55.6%	59.8%	65.0%
Traffic 5k-15k AADT [km]	4.9%	11.0%	7.4%	9.5%
Traffic >15k AADT [km]	0.2%	0.0%	0.1%	0.1%
N lanes = 1 [km]	72.2%	43.6%	53.6%	55.8%
N lanes = 2 [km]	19.0%	19.7%	16.2%	16.9%
N lanes = 3 [km]	0.1%	2.5%	1.8%	2.0%
N lanes $\geq$ 4 [km]	0.1%	0.1%	0.1%	0.1%
Traffic signals [n]	32	0.89	1.12	1.62

Note: Only the gradient attribute has full network coverage and the probabilities correspondingly add to 100%.

Generally, the patterns between the shares of attributes along the shortest and chosen routes reveal mostly anticipated preferences. Considering the bike path, no measurable trade-off can be observed due to the very scarce availability of such paths, especially in the urban areas. The share of mixed bike paths is slightly higher on the chosen routes, while the share of bike lanes is substantially smaller as in the shortest routes. Looking at the speed limits, one can see that the shares for speed limits of 50kph and greater are smaller in the chosen routes. Intuitively, the share of streets limited to 30kph is higher on the chosen routes.

The gradient levels show higher shares along the chosen routes for gradients up to 2%, and lower ones for gradients between 2% and 10%. Gradients above 10% don’t show any difference between chosen and shortest routes, which is due to the respective links being peripheral and rather irrelevant for the allover network connectivity. Other unfavorable attributes such as traffic volumes over 5k AADT, and (inherently correlated) streets with more than two motorized lanes show lower shares in the chosen routes. However, it must be noted that streets with more than 15k AADT traffic volumes, as well as with more than two motorized lanes only represent a negligible part of the network. Finally, the average number of traffic signals along a path is higher for the chosen routes. The behavioral interpretation of traffic signals is ambiguous and it is not clear whether this represents a positive or negative attribute. From a negative perspective, traffic signals do to some extent serve as proxies for large complex intersections, which are objectively unfavorable. However, they could also have some (random appearing) spatial correlation with another positively perceived attribute.

Estimation results The model estimation results are shown in Table 4.9. We estimated two separate PSLs based on the utility function 4.3, one containing only base parameters (see Table 4.8), the other additionally containing interaction effects onto the base parameters. The interaction effects are included as binary dummy variables and cover the three available type of bikes (regular bike, E-bike, S-pedelec), the gender and the age. The latter is binary encoded into older/younger than 40 years.

For the simple model, all parameters have to be considered in relation to the reference alternative. The reference alternative constitutes of a street with two motorized lanes, without cycling infrastructure, a speed limit of 50kph, and a gradient smaller than 2%. The parameters mostly show the expected signs. The length parameter is negative and significant which is a commonly used indicator for the behavioral validity of route choice models (i.e. utilitarian cyclists prefer a shorter over a longer route). The estimates for the cycling infrastructure parameters do not align with the insights suggested from the descriptive analysis. The bike path parameter is negative and significant, but effectively very small. As previously mentioned, bike paths are very scare in the network and not present in the main urban areas. It must be assumed that the choice sets do not include enough observable trade-offs for the model to derive meaningful behavioral parameters. An actual negative perception of bike paths would be counter intuitive and not backed by any relevant literature. The mixed bike path parameter negative as well but not significant. As opposed to regular bike paths, it seems like the choice sets would include enough observable trade-offs. The negative estimate is probably rather due to the spatial distribution of such paths (mostly in rural parts) and the availability of these paths to pedestrians, for which the literature typically reports a negative perception. The bike lane parameter is positive and significant. This is not suggested by the descriptive analysis but intuitive and according to literature considering that bike lanes are the most relevant type of cycling infrastructure in the network (w.r.t. extent and spatial distribution).

The estimate for lower speed limits is negative but not significant. This is not intuitive and against what the descriptive statistics suggest. The reasons for that are unclear; potentially a lack of trade-offs in the choice sets or underlying multicolinearity. The estimate for higher speed limits is negative as well, which is intuitive. The estimates for the different gradients show the expected signs and are all significant. The relative spread between the estimates is aligned with the results from previous studies for Switzerland (Meister et al., 2023) and reflect the distinct topological conditions compared to other e.g. European cities. The traffic volume attribute could not be modeled, as it created numerical instabilities during the estimation process. This is most likely due to the imbalance of the corresponding attribute levels in the network. The estimates for the number of motorized lanes are intuitive and as expected. Compared to the reference street with two motorized lanes (independent of directions), the parameter for having only one motorized lane (i.e. a one-way street) is positive (however not significant). The parameters for having three motorized lanes are negative and significant, and grow even more negative when increasing to four or more lanes.

The estimate for traffic signals is negative but not significant. Considering that traffic signals serve as proxies for large intersections, the negative estimate is rather intuitive. It, how-

Table 4.9: Estimation results for the Aarau models.

	PSL_1		PSL_2	
	est.	std.	est.	std.
Length	-1.74***	-4.56	-1.79***	-4.75
Bike path	-0.07*	-1.66	0.74*	1.65
S-pedelec			-0.59*	-1.914
E-bike			-0.07	-1.37
Older $\geq$ 40			2.71***	2.57
Bike path mixed	-0.23	1.60	0.78	1.41
S-pedelec			-0.70***	-3.65
E-bike			-0.37**	-2.14
Older $\geq$ 40			0.80	1.56
Male			-0.81*	-1.77
Bike lane	0.88**	1.96	0.35*	1.85
Older $\geq$ 40			1.47***	2.81
Speedlimit $\leq$ 30kph	-0.24	-1.59	-0.17**	-2.17
S-pedelec			-1.75**	-2.08
E-bike			-2.63***	-3.41
Speedlimit >50kph	-1.39**	-2.10	-2.03***	-2.36
S-pedelec			4.49***	2.92
E-bike			2.33**	2.08
Male			2.55**	2.12
Slope 2-6%	-0.89*	-1.83	-0.59	-1.34
S-pedelec			0.62	1.52
Slope 6-10%	-3.05***	-2.95	-1.53**	-1.83
S-pedelec			0.83*	1.82
Slope >10%	-5.08**	-2.21	-9.67***	-3.98
N lanes = 1	0.55	1.17	1.52**	2.10
S-pedelec			-1.27	-1.47
E-bike			-1.67***	-2.33
N lanes = 3	-0.95*	-1.78	-0.86	-1.05
N lanes $\geq$ 4	-1.91*	-1.70	-3.76**	-1.86
E-bike			5.11**	2.17
Traffic signals	-0.04	-1.45	-0.13	-1.30
PS	3.09***	27.29	3.10***	25.05
Parameters	14		64	
Final LL	-6'352.96		-5'850.64	
AIC	12'733.88		11'829.28	
BIC	12'722.40		11'717.76	
Rho2	0.54		0.57	

Note: ***p<0.01, **p<0.05, *p<0.1 using robust standard errors.

ever, reverses what is suggested by the descriptive analysis. The actual behavioral interpretation of traffic signals remains unclear, especially as one has to assume multicolinearity with other relevant choice attributes. Finally, the parameter for the PS metric is positive and highly significant. This is according to theory and indicates a substantial amount of overlap within the choice sets.

The second model includes interaction effects for socio-demographics and the type of bikes, totaling in 64 model parameters (as opposed to 14 in the first one). The reference level for these parameters are female respondents under 40 years of age with a regular bike. We only show the interaction parameters that are (close to being) significant at the 10% level. The fit-of-model indicators listed at the bottom of Table 4.6 show a increase in model fit. The base parameters mostly show the same patterns w.r.t. estimate sign and significance as for first model.

The most notable differences are related to the cycling infrastructure parameters. The estimates for mixed and regular bike paths turned positive, the latter being significant, and both being larger than the bike lane estimate. This is clearly more intuitive and comparable to the literature. The interactions reveal a substantial amount of heterogeneity for the preferences; for E-bike and S-pedelec users, the positive perception of (mixed) bike paths is reduced, which makes sense considering their higher speeds and (typically) reduced aversion to mix with motorized traffic. Furthermore, the positive perception of any infrastructure type is increased for users older than 40 years, which also seems intuitive. The signs of the interaction effects of E-bikes and S-pedelecs onto speed limits are intuitive and expected; the higher speeds of such bikes decrease the utility of low speed limits, and increase the utility for higher ones. Nevertheless, the effect size seems rather large. A similar, reasonable pattern can be observed for the interaction effect of these bikes onto the number of motorized lanes, considering that the number of motorized lanes correlates with traffic volumes and speed. Just as with speed limits, the actual effect size, e.g. of E-bikes onto streets with four or more motorized lanes, seems oddly large and is probably slightly overestimated. Finally, there are interaction effects of E-bikes on the two first gradient levels. Both compensate the negative perception of these grades, where the effect increases with the grade.

4.1.4 Comparison

The models presented for the three focus areas of this study show substantial differences in their parameter estimates. These estimates cannot be directly compared across the models due to scale variance in the different datasets (i.e. choice sets). The actual effect size of a certain attribute in the utility function can be compared across models by evaluating the respective marginal rates of substitution. In the context of route choice models, one typically calculates Value-of-distance (VoD) indicators. They represent how much distance would be traded for more/less of a certain attribute along the route. For the case of linear-in-parameter model specifications, the VoDs are given by the ratio of parameter i and the length parameter. Any VoD above/under 0 is considered to increase/decrease the perceived length by VoD%. The resulting indicators are shown in Table 4.10.

Table 4.10: VoD indicators for the different models.

	Zurich	Basel	Aarau
Bike path [km]	-0.12	-1.06	0.04
Bike path mixed [km]	-0.68	-0.62	0.13
Bike lane [km]	-0.50	-0.37	-0.50
Speedlimit <=30kph [km]	-0.28	-0.12	0.13
Speedlimit >50kph [km]	0.35	0.34	0.79
Slope 2-6% [km]	0.40	0.68	0.51
Slope 6-10% [km]	2.23	2.76	1.75
Slope >10% [km]	7.38	4.40	2.91
Traffic 5k-15k AADT [km]	0.22	0.07	-
Traffic >15k AADT [km]	1.54	2.10	-
N lanes = 1 [km]	0.37	-0.10	-0.31
N lanes = 3 [km]	1.36	0.15	0.54
N lanes >= 4 [km]	0.16	0.61	1.09
Traffic signals [n]	-0.05	-0.09	0.07

The indicators for the three areas are computed using the base parameters of the simple models (those without interaction terms). The derived indicators are hence valid for an average respondent of each sample. As shown in Table 4.1, 4.4 and 4.7, the respondents from the different areas are generally comparable w.r.t. their socio-demographic characteristics, i.e. they are all biased in the same way towards being rather male, slightly older, better educated, and with higher income.

When comparing the preferences across the different areas of interest, one has to carefully evaluate what actually causes the differences in derived preferences. Generally, one could assume that respondents from the different areas have different preferences which relate e.g. to the size/density of the city (Aarau is much smaller than Basel and Zurich) or a different local cultural context (which seems less plausible). On the other hand, one also has to consider the respective network composition, as deriving preferences from observed choices, assumes that these choices are made consciously. However, they might just be "forced" by the local network conditions (extent and spatial distribution of attributes), e.g. if there is no existing cycling infrastructure, respondents do not actively choose not to use those.

The VoD indicators show that, in general, cycling infrastructure is the most positively perceived network attribute. However, there are considerable differences across the three areas in terms of the actual type of infrastructure preferred. Bike paths are what the literature generally considered the most attractive infrastructure type. This pattern can be found in Basel, which is interesting as bike lanes are much more prominent in the core urban area. For Zurich and Aarau, the bike path VoDs are the smallest compared to other types (and even positive, i.e. negative perception, for Aarau). This is most likely due to the scarce availability of such paths in the network as opposed to an actual difference in preferences. For Zurich, mixed bike paths have the highest VoD and are basically on the same level as for Basel. This is intuitive, as the extent and spatial distribution of such paths can be considered similar for both networks. For Aarau, the indicator suggests a negative perception and small allover relevance. The configuration of such paths is, however, similar to the larger cities, i.e. the paths are mostly outside the dense urban zones and connect those to surrounding sub-urban or rural areas. A fundamentally different preference of such paths for residents of small cities could be a potential explanation. The VoDs for bike lanes are comparable across the three areas, with Basel having slightly smaller values. For all three areas, bike lanes represent the most prominent type of infrastructure in the urban cores.

The preferences patterns for speed limits are comparable for Zurich and Basel, i.e. low speeds decrease the perceived distance and higher speeds increase it. For Zurich the preferences seems to be slightly more sensitive for low speed streets, even though the network does have more of such streets. For Aarau, one can observed a substantially higher negative perception for higher speed limit streets which can potentially be attributed to the comparably high share of such streets in the network. The VoDs for different gradient levels have the same patterns across all cities, however with Zurich and Basel showing higher sensitivity for gradients larger 6% and Zurich being even more sensitive for gradients larger 10%. While the network for Basel includes slightly more streets steeper than 6%, the core urban area (i.e. the canton of Basel Stadt) is comparably flat, with the maximum elevation difference of around 280 meters only. On the other hand, the city of Zurich has elevation differences of up to 450 meters. One can therefore assume that the increased sensitivity in Zurich is related to the spatial distribution of steep links and their relevance for the network connectivity. The city of Aarau only has an elevation difference of around 100 meters, which potentially explains the smaller sensitivity for gradients.

The indicators of traffic volume levels are only available for Zurich and Basel, as the corresponding parameters could not be estimated for Aarau. The values have the same patterns, whereas the Basel area shows a greater sensitivity towards traffic volumes greater than 15k AADT. No explanatory conclusion for this can be derived when comparing both network compositions.

The preference pattern w.r.t. the number of motorized lanes are comparable for Basel and Aarau. Both have a positive perception of one-way streets, and an increasing negative perception for every lane added to the two-lane reference street. The composition of both networks are almost identical w.r.t. the shares of motorized lanes. Consequently, the slightly higher sensitivity (in both directions) in Aarau could either be due to the observed choices being influenced by the network composition, or the respondents of Aarau generally being more sensitive. For Zurich, the VoDs reflect the previously mentioned non-intuitive patterns found in the model parameter estimates, which are mostly likely due to the network. This is seems especially plausible for streets with four or more motorized lanes, which in Zurich, are present at many important bottlenecks (i.e. mostly bridges).

Finally, the preferences for traffic signals reflect the previously mentioned ambiguity w.r.t. the behavioral interpretation. While the VoDs are all comparably low, they indicate a positive perception in both Zurich and Basel, but a negative one for Aarau. This suggest an underlying dependency of the city size, maybe linked to the network which contains a far greater density of traffic signals for Zurich and Basel when compared to Aarau.

4.2 Stated preferences

To complement the observed preferences on cycling infrastructure, a stated-preference (SP) experiment was conducted as part of this project. The SP-experiment is intended to further study the cyclists' (as well as non-cyclists') preferences toward cycling infrastructures. One of the limitations of RP-data is that sometimes, not all alternatives are actually available for choice. Concretely, on certain routes there are sometimes not really alternatives available and the revealed preferences can become biased due to that. On top of that, SP data allows us to throw light on possible improvements in cycling infrastructure in Switzerland, by including routes with cycling infrastructure qualities which are existing today.

A main characteristic of the experiment made, is that the individuals have to trade-off cycling infrastructure quality attributes against travel times, which adds more information, by forcing individuals to not only state their absolute preference, but also how much they are willing to pay (in terms of lost time here) for traveling through a better cycling infrastructure.

Because the SP survey was based on hypothetical situations and the picture material is generated artificially, we do not engage in a region-specific analysis of the data.

4.2.1 Methods

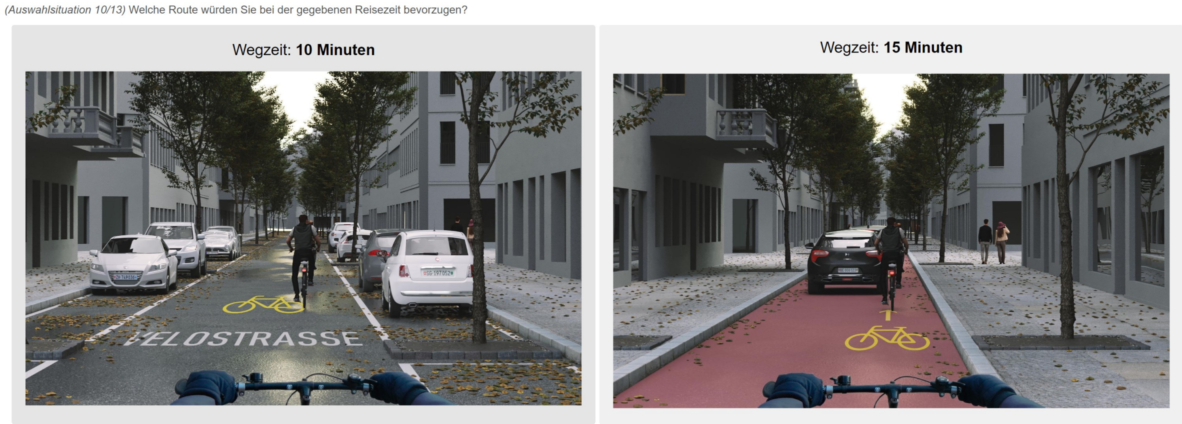
Participants of all the groups in the EBIS study were invited to participate in this SP-experiment. Since our sample consists of cyclists, and it is also important to also understand the preferences of non-cyclists alike, we additionally recruited 500 participants who do not cycle, through a panel.

The studied cycling infrastructure attributes 4.11 were varied by generating a d-optimal choice design with the software Ngene. This allows the number of combinations and necessary choice situations to be minimized. Each respondent was requested to state a choice in a total of 13 choice situations among two alternatives. The experiment was split into main-street alternatives, neighborhood-street alternatives as well as choices between a main and a neighborhood street 4.4

Table 4.11: Attributes varied in the SP-experiment

Variables	**Neighborhood street**	**Main street**
Car traffic intensity	Low/High	Low/High
Speed signalisation	No variation	30 km/h / 50 km/h
Travel time (min)	7/10/15	7/10/15
Car parking	Yes/No	Yes/No
Cross-section	No variation	Cycling lane/Cycling path
Cycling lane phys. Separation to car lane	Not applicable	Painted lane/Physical elements/Buffer zone
Neigh. Street markings	No marking/Small bike symbol on side of the lane/Large symbol and "Cycling street" marking on street/Red painted road with bike symbol (dutch-style)	Not applicable
Cycling lane/path width	Not applicable	1.5m/2.2m

Figure 4.4: Example of choice situation



4.2.2 Modelling approach

Our goal is to show how different groups evaluate cycling infrastructure differently, that is, how different groups evaluate the variables in the choice model differently. This is a different evaluation than that usually encountered in a choice-modeling setting in which the modeler is interested in understanding how the explanatory variables impact the choice of an alternative. Here we only have two alternatives: main or neighborhood streets. The choice among both is only examined in one of the three experiments, in which we compare main and neighborhood streets. In the remaining experiments, the alternative, and therefore the alternative-specific constant is the same. In these experiments, the focus lies on the evaluation of infrastructure features. We chose a pragmatic approach of partitioning our dataset into the groups of interest and estimating an individual model for each partition. The equation below shows the multinomial logit model formulation.

$$U_{i,e,WTP} = SP_e \cdot (ASC + \beta_{tt} \cdot age/avg.tripdist. \cdot (tt + \sum_j WTP_j k_j)) \qquad (1)$$

Where:

SP_e is the scaling parameter for each of the 3 experiments ASC is the alternative specific constant i is the group j for each k feature k is the feature under study β_{tt} and tt are respectively the travel time parameter and variable WTP_j is the willingness-to-pay for each feature age Is the individual's age. $avg.tripdist.$ Is the average trips distance of an individual.

The sociodemographic variables used are gender and age, the former being used for dataset partitioning and the latter in the model formulation as a variable interaction with the utility function, to capture the effect of age in the preferences of individuals. We also use the average trip distance by bike of each individual in the model, which we obtained from the tracking part of the study as a mean to control the estimates for the exposition to cycling infrastructure that each individual has.

4.2.3 Results of the stated preference models

4.12 shows the results of the partitioned MNL choice models. The preferences are shown in terms of willingness-to-pay in terms of minutes of travel time loss that are willing to be incurred to ride through a certain infrastructure feature quality, compared to a reference quality level. For the interpretation of the WTP we highlight that positive values indicate how much additional travel time cyclists are willing to pay to avoid a certain element, while negative values indicate how much additional time cyclists are eager to incur to cycle on a route with the corresponding attribute. We therefore color the cells of the WTP values in 4.12 in green and red to represent each infrastructure's positive and negative outcomes. Variables were kept in the model if the resulting parameters were significant at the 25% level at least for at least one model partition. The conventional bike group only includes frequent riders, since our sample of sporadic conventional cyclists only included 35 individuals.

To improve the readability of results, 4.5 to 4.10 compare the highest WTP values across the groups in a graphical form and include images of the differences in the evaluated street design elements.

Table 4.12: Model results (green shading: positive variable effect, red shading: negative effect)

					Conv. Bike		E-Bike (25 km/h)				S-Pedelec (45 km/h)			
			Non-cyclist		Frequent		Sporadic		Frequent		Sporadic		Frequent	
Variable			Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
General	Experiment scaling parameters	Both	1.0 NA	1.0 NA	1.0 NA	1.0 NA	1.0 NA	1.0 NA	1.0 NA	1.0 NA	1.0 NA	1.0 NA	1.0 NA	1.0 NA
		Main street	1.1 ***	1.5 ***	1.7 ***	1.7 ***	1.3 ***	1.4 ***	1.1 ***	0.9 ***	1.1 ***	1.1 ***	1.7 ***	1.2 ***
		Neigh. street	0.6 ***	0.7 ***	1.2 ***	1.3 ***	1.2 ***	0.7 ***	1.1 ***	0.9 ***	1.1 ***	0.8 ***	1.3 ***	0.8 ***
		ASC neigh. street	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA
		ASC main street	0.6 ***	1.1 ***	0.6 ***	0.6 ***	0.7 ***	0.7 ***	0.3 ***	0.1	0.7 ***	0.6 ***	0.4 ***	0.5 ***
		Travel time	-0.003 ***	-0.001 ***	-0.013 ***	-0.008 ***	-0.008 ***	-0.008 ***	-0.011 ***	-0.010 ***	-0.013 ***	-0.011 ***	-0.014 ***	-0.011 ***
Neigh. street WTP [min] variables	Traffic	High	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA
		Low	-8.1 ***	-23.0 ***	-5.8 ***	-4.9 ***	-6.5 ***	-8.0 ***	-4.4 ***	-5.2 ***	-5.1 ***	-2.9 **	-3.7 ***	-5.4 ***
	Parking	Yes	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA
		No	-1.0 *	-13.3 ***	-5.0 ***	-6.0 ***	-6.8 ***	-6.1 ***	-4.2 ***	-5.2 ***	-3.8 ***	-5.5 ***	-3.4 ***	-4.5 ***
	Street markings	No markings	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA
		Bike symbol	0.3	3.4	-1.5 **	1.1	-2.0	1.8	-0.6	0.4	0.0	0.6	-0.8	-3.4 '
		Cycling road with large bike symb.	-0.7	3.3	-2.7 ***	-3.6 ***	-1.0	0.1	-1.0	-4.8 **	-3.6 **	-1.0	0.0	0.0
		Bike symbol and red paint	-1.5 '	-12.2 **	-1.3 *	-1.1	-0.8	-1.5	-1.2 '	-5.0 **	-2.0 '	-6.4 *	-1.9 *	0.5
Main street WTP [min] variables	Infrastructure type	Cycling lane	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA
		Cycling lane with buffer	-2.0 **	-6.8 **	-0.6 '	-1.8 **	-0.3	-2.4 **	-1.2 '	-2.9 *	0.5	-1.6	0.9 '	-1.4
		Cycling path	-5.8 ***	-22.9 ***	-4.5 ***	-6.7 ***	-6.3 ***	-9.5 ***	-6.2 ***	-11.5 ***	-6.0 ***	-7.8 **	-2.8 ***	-3.1 '
	Lane/path width	Narrow	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA
		Wide	-2.2 ***	-1.4	-3.1 ***	-2.5 ***	-4.4 ***	-3.2 ***	-4.1 ***	-3.2 **	-4.1 ***	-3.8 *	-2.8 ***	-1.7 '
	Cycling lane separation	No physical separation	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA
		Physical separation without parking	-1.7 *	-0.3	-0.4	1.0 '	-1.4	-3.1 ***	-3.1 ***	-1.1	-0.9	7.6 **	2.0 **	1.3
		Physical separation with parking	-3.8 ***	-3.8	-1.2 **	-1.4 *	-1.8	-4.3 **	-1.4 *	-4.0 *	-0.2	-2.5	-1.0 '	2.2
	Infrastructure type interactions	Wide cycling lane x Physical separation	2.4 **	-3.3	0.7 '	-0.3	2.1 '	3.6 **	0.8	-0.7	-1.4	-2.8	-0.3	-2.4 '
		Cycling lane x Speed limit 30 km/h	-1.7 '	-4.7 '	-0.7	-1.1	-1.6	-2.2 '	-0.5	-1.0	1.6	-0.5	0.4	-1.9
		Cycling lane x Traffic low	2.0 *	-0.4	-0.5	-0.8	1.5	-2.1 *	0.0	1.0	2.0 '	0.9	0.4	2.3
	Speed limit	50 km/h	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA
		30 km/h	-0.7	-3.9 '	-0.6 '	0.2	-1.1	-0.2	0.1	-0.4	-0.6	-0.8	-0.6	-1.2
	Traffic	High	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA
		Low	-0.5	-0.7	-0.4 '	-0.3	-0.8	0.6	0.0	-0.8	0.0	-0.5	-0.4	-0.9
	Parking	Yes	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA	0.0 NA
		No	-3.8 ***	-10.9 ***	-3.6 ***	-4.6 ***	-2.7 ***	-4.9 ***	-4.6 ***	-8.1 ***	-4.5 ***	-10.4 ***	-3.6 ***	-4.0 ***
		Individuals	268	245	524	282	137	166	295	123	256	158	254	121
		Adj. Rho squared	0.12	0.16	0.25	0.23	0.21	0.22	0.21	0.22	0.14	0.17	0.18	0.17

Sign. codes: 0***0.001**0.05*0.10'0.25

4.2.4 The roles of gender and cycling frequency

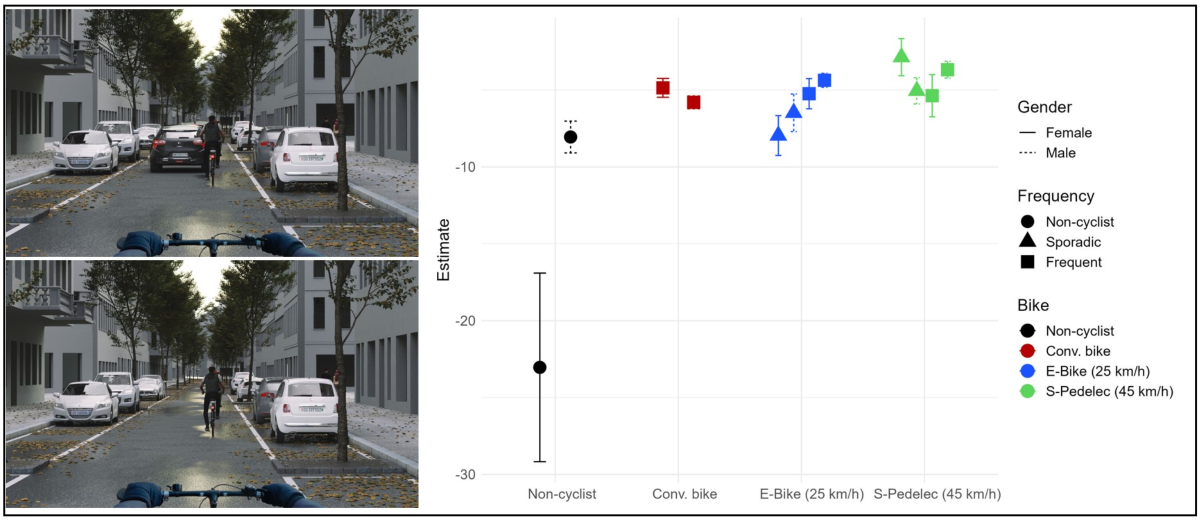
The first obvious effect is that the group most sensitive to street design elements are females who do not cycle. Interestingly, gender seems to play a greater role than cycling frequency and bicycle type for the preferences. Across the other groups, females often, but not always, also seem to be more sensitive to differences across the experiment variables. The cycling gap between males and females has been widely studied in the literature. Studies focusing on safety aspects of cycling have consistently found that women have higher safety concerns and are more risk averse than men (Delmelle and Delmelle, 2012; Manton et al., 2016) leading them to show greater sensitivity to build environment and streetscape variables than men (Mitra and Nash, 2019; Hardinghaus and Weschke, 2022b). Interestingly men who do not cycle have preferences closer to individuals who do cycle than to women who do not cycle, which may be explained by the lower perceived likelihood of negative outcomes in potentially risky situations (in this case traffic accidents and dangerous situations) that men have compared to women as reported by (Harris and Jenkins, 2006).

The studies mentioned above do not quantify the differences among men and women while controlling for differences in cycling frequency, though. Part of the differences in WTP among men and women, at least, as well as WTP differences across different bike types should be attributed to the amount of exposure to street environments when cycling. We account for this in the models by interacting all variables with the average trip distance of individuals. Still, gender differences are visible in the models, showing that not all differences in preferences can be attributed to the different exposure to street environments when cycling. The figure shows that across all groups, females ride bicycles less than men, which should at least partly explain why females have higher WTP's than men. Frequent S-pedelec riders ride the bike the most. Sporadic S-pedelec riders, frequent E-bikers and frequent conventional cyclists all ride the bike for similar distances.

The difference in WTP's between men and women is significant for some of the street design elements. Non-cycling women are twice as sensitive to traffic in neighborhood streets than non-cycling men 4.5. The difference increases to three- to fourfold than that of men for other street design elements namely parking in neighborhood streets 4.6, and distinctive cycling street markings in neighborhood streets 4.7, bike paths 4.8 and UFO-style physical separators for cycling lanes 4.10. Such substantial differences show how much greater the sensitivity of women is towards cycling-friendly infrastructure and partially explain why women are 28% less likely than men to cycle in Switzerland (Meyer de Freitas and Axhausen, 2022). The greater confidence interval in the WTP of female non-cyclists also points towards a greater heterogeneity in the preferences of this group compared to male non-cyclists. The similar sample size in the male and female non-cyclist group excludes the possibility of sample size being an explanation for the higher variability in female preferences.

Among frequent or sporadic cyclists, females often have a higher WTP for cycling-friendly street designs than men. As with non-cyclists, females in these groups also have a higher variability in their preferences when compared to men. The WTP of women is most pronounced in the preference of female E-bikers and conventional cyclists towards cycling paths 4.8, as well

Figure 4.5: WTP by groups for car traffic reduction in neighborhood streets.



as in the preference of female E-bikers and conventional cyclists towards UFO-style physical separators for cycling lanes 4.10. Frequent female E-bikers have a higher WTP than men for all elements in the figures below except for bollards in cycling lanes 4.9. Sporadic female and male E-bikers are more similar in their preferences, although the preferences of females in the sporadic E-bikers group mostly follow the preferences of their frequent cyclist's counterparts for most of the evaluated elements as well.

Among S-pedelec riders, we find that the differences between male and female preferences are closer together than for E-bikers, which is visible by the higher degree of overlap of the confidence intervals in the figures below for these groups. This is more noticeable for frequent S-pedelec riders, a group for which female and male preferences differ less than among other groups. For sporadic S-pedelec riders, the differences are less pronounced than among frequent S-pedelec riders, with a substantial difference in the WTP for bollards in cycling lanes 4.9. Males and females riding conventional bikes, all of whom are frequent riders in our dataset, have preferences that are significantly different for all elements besides for red-painted neighborhood streets 4.7. Still, while being significantly different, the differences in WTP are smaller than the difference in preferences across E-bikers and S-pedelec riders.

Comparing the preferences across all groups, we find that the sporadic E-bikers group has the strongest preference for cycling-friendly neighborhood streets and frequent E-bikers have the highest WTP for cycling paths, with females within these groups having higher WTP's than men 4.12.

The role of street designs

After looking into how cycling frequency and gender influence the preferences for cycling-friendly street designs, we turn back to 4.12 to evaluate how these preferences vary for the different street design elements.

Across all elements, it becomes evident that three design elements are consistently preferred among all groups, namely low-traffic neighborhood streets 4.5, neighborhood streets

Figure 4.6: WTP by groups for car parking removal in neighborhood streets.

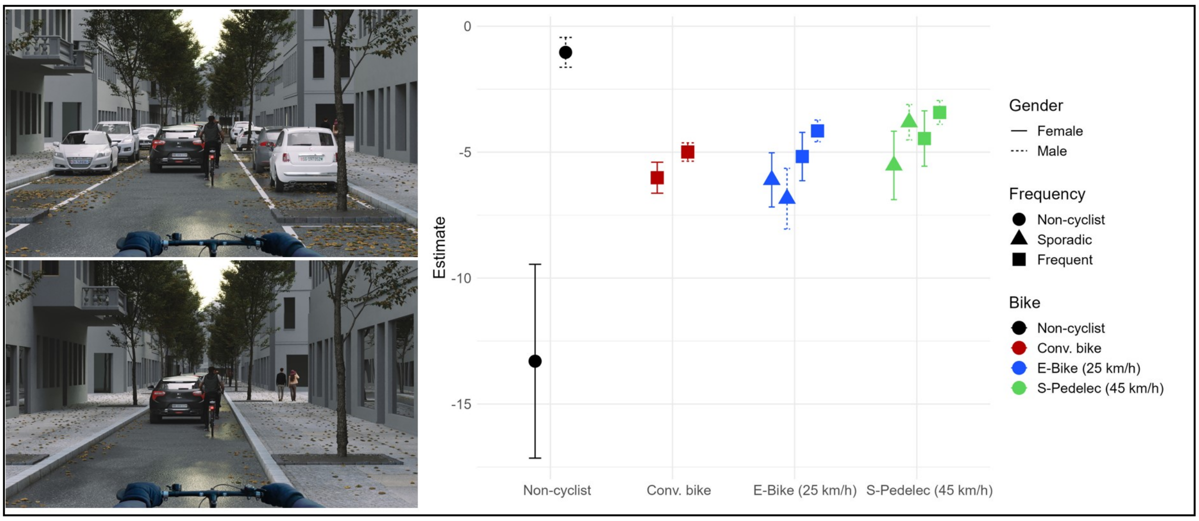


Figure 4.7: WTP by groups for bike symbol and red paint markings in neighborhood streets.

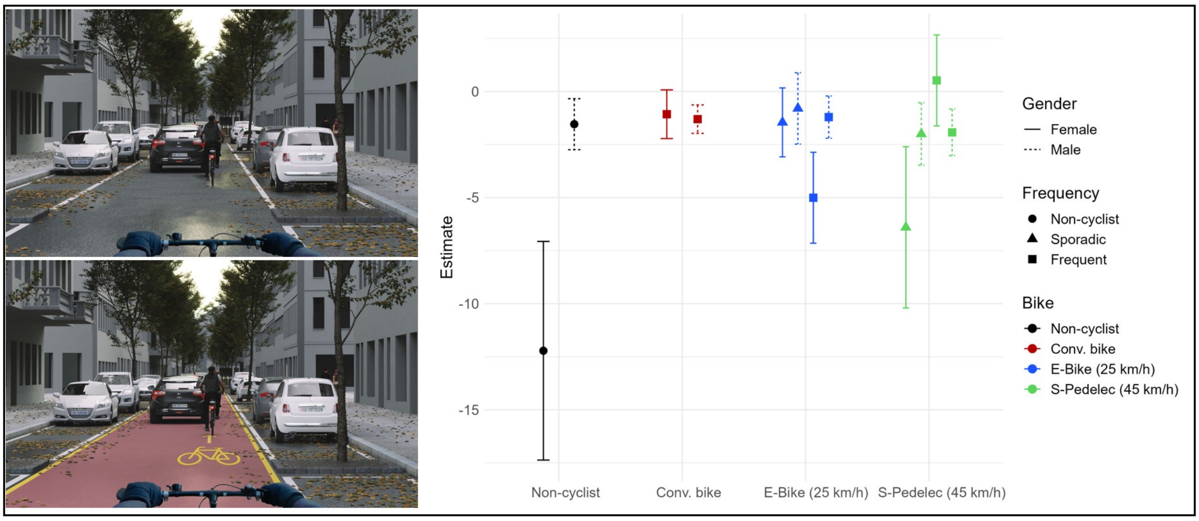


Figure 4.8: WTP by groups for cycling path instead of cycling lane in main streets.

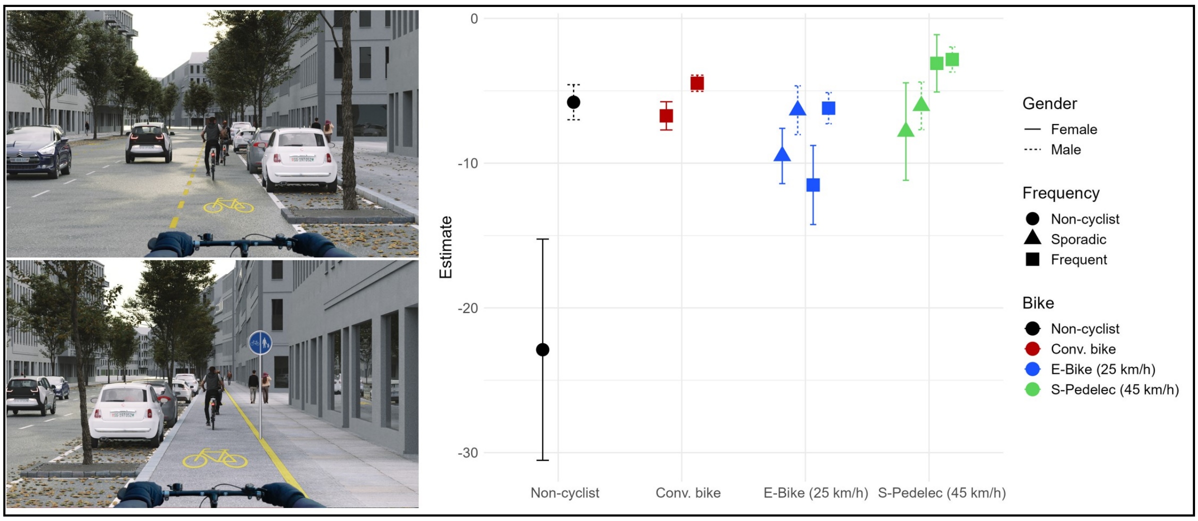


Figure 4.9: WTP by groups for physical separation without parking (bollards) instead of no physical separation with parking.

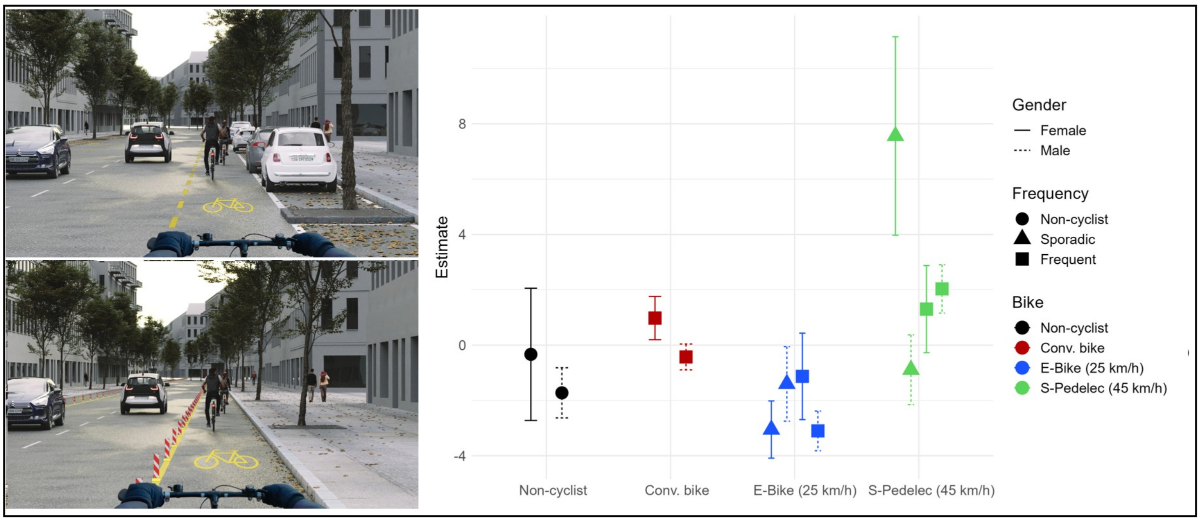
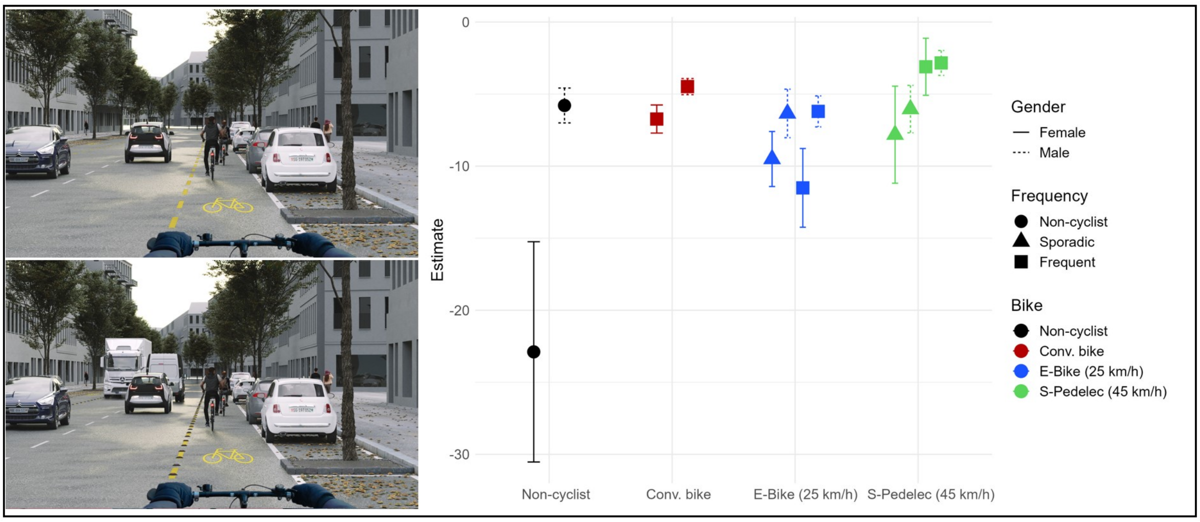


Figure 4.10: WTP by groups for physical separation with parking instead of no physical separation with parking.



without parking 4.6, and cycling paths instead of cycling lanes on main streets 4.8 as well as no parking on main streets (for cycle lanes) and wide cycling lanes. In the literature, cycling paths are often found to offer the safest and most comfortable cycling infrastructure, which our findings corroborate, albeit not for all studied groups. Cycling paths have a high subjective safety perception because bikes are separated from motor vehicle traffic, reducing conflict frequency and therefore increasing subjective safety feelings (Gössling and McRae, 2022). It is interesting to note that the high WTP's for no parking, low traffic on neighborhood streets and wide cycling lanes are all elements that reduce potential conflicts with motorized traffic and come close to this "gold standard" of cycling infrastructure. While this general direction in preference is not unexpected nor surprising, the difference in preference for these different street design elements across the different individuals becomes more interesting.

Albeit scoring highest for most groups, cycling paths do not have the highest WTP across all groups. It certainly is for non-cycling females, for example, the group that cycles the least. Therefore, if a policy goal is to increase cycling adoption across society, cycling path expansion is a promising policy. Cycling paths are also the most preferred cycling-friendly design element for frequent E-bikers and female sporadic E-bikers and conventional cyclists as well as male sporadic S-pedelec riders. Frequent S-pedelec riders still value cycling paths, but they place more value at having lower traffic and fewer parked cars in neighborhood streets. This might be related to the fact that such S-pedelec bikes ride at faster speeds and that conflicts with cars become more of a nuisance for these individuals in low-speed neighborhood streets. At the same time, the WTP of S-pedelec riders for these elements is still lower in value than that of E-bikers and conventional cyclists.

We also investigated the effects of different neighborhood street designs. While the alternative-specific constant for main streets, shows that this type of street is preferred against neighborhood streets, possibly because they are associated with faster connections and more direct paths, our results also show that significant improvements for cyclists can be gained by improving neighborhood street designs. Notably, the highest WTP are associated to the removal of car traffic from neighborhood streets, rather than the "cosmetic" nudging effect of introducing street markings. Every group has types of street markings that have insignificant effects, with E-bikers having no visible effect for all street markings. This very weak effect shows that "hard" design elements which do reduce conflicts with cars have a stronger effect than the softer nudging effect of such street markings.

Another specific design we tested, was physically separated cycling lanes, which became very popular during COVID-19 as pop-up bike lanes. We find mixed results for physically separated cycling lanes. We tested two types, namely with bollards 4.9 and with UFO-style separators 4.10 which would still allow for cars to access parking spots. The alternative with bollards has a positive WTP for some S-pedelec riders and is statistically indifferent to cycling lanes for most of the other groups. Preferences are generally higher towards the alternative with UFO-style separators. We can only conjecture why some S-pedelec riders seem to dislike bollards as physical separators. One plausible explanation is that these riders often overtake other cyclists and having such physical obstacles makes such overtaking maneuvers substantially more dangerous through an increased crash risk.

4.2.5 Policy implications of the stated preference survey

Cycling paths, especially wide ones are the preferred cycling infrastructure, providing the highest level of both subjective and objective safety. These should therefore unequivocally be advanced by cycling advocates and public authorities alike. This finding is not new and reflects decades of research on the topic. Our results add to the literature the knowledge that this preference is highest among non-cycling females, the group that cycles the least and should therefore be a priority target-group in policies aiming to increase overall cycling adoption in society. While the WTP of low traffic in neighborhood streets is a decimal point lower than that of cycling paths, the higher alternative-specific constant of main streets pushes the overall utility of this type of infrastructure upwards. Also, we remind the reader, that our reference level for main streets are already cycling lanes, which are commonly found in Swiss main streets. In contexts where main streets have no cycling infrastructure at all, the WTP for cycling paths is therefore expected to be higher still.

Still, while providing a higher benefit overall when comparing individual interventions, the combined utility of removing car parking and car traffic in neighborhood streets does lead to a significant increase in the attractiveness of neighborhood streets for many of the groups evaluated. For example, the total utility of a neighborhood street without any car traffic or parked cars is only 14% lower than that of a cycling path[3] for non-cycling females. If the asphalt is painted red and bike symbols are added, the total utility of neighborhood streets becomes even 15% higher than that of a main street with a cycling path. Improvements in neighborhood streets can thus lead to a similar or equal attractiveness level.

[3] Utilities calculated with average values for age, travel time and travel distance.

In sum, we observe that in general, the highest WTP's are in place for street designs where potential conflicts between cars and cyclists are reduced as much as possible. Nevertheless, our results show that there is substantial heterogeneity in how strongly different cycling groups value this separation, which we highlighted through the WTP values as well as in the order of preference for different street designs. The frequency of bike utilization, gender, and type of bike play significant roles here. Frequent S-pedelec riders were found to place the least value on cycling-friendly street designs, having an especially low WTP for cycling paths. This makes sense since with 45 km/h of maximum speed such S-pedelecs are running at speeds that are de-facto as high as the speed of cars in urban environments, whilst the high power of such S-pedelecs also allows these individuals to accelerate quickly and keep a traffic flow that is not too different from that of cars. Anecdotally, some S-pedelec participants of the EBIS study actively wrote to the authors of this study with the request for us to consider the differing nature of their needs with respect to cycling infrastructure when compared to their E-bike and conventional bike counterparts.

Some of these messages alluded to the fact that S-pedelecs are treated by Swiss law in a similar way as bicycles, which requires them to use cycling infrastructure, when available. While the WTP for cycling paths, for example, is the lowest for this group, it is still positive and significant, meaning that while some S-pedelec riders do not prefer to ride on cycling paths, most of them do prefer this alternative.

Concerning the physical protection of bike lanes from car lanes, we find that when bollards are used, many of the groups see little to no improvement from a situation without them, with two groups finding these even worse than no physical separation. This finding contradicts the findings from (von Stülpnagel and Binnig, 2022) who conducted a study in Berlin using very similar images as ours albeit with different designs of bollards. Possibilities for the differences are the study design, ours being an SP study and von Stülpnagel and Binnig (2022) being based on ratings of individual situations as well as a different composition of respondents or even, different experiences in traffic by the respondents. Possibly respondents in Berlin, a metropolis with higher traffic volumes and higher population density than in the Swiss context, makes respondents more sensitive to being separated from car traffic. The situation is different in the case of UFO-style separators, which are preferred against cycling lanes without them, possibly because they offer less collision danger, by allowing bikes to ride over them when, for example, overtaking other cyclists. We therefore recommend that municipalities conduct live trials with such separations and conduct interviews with both cyclists and non-cyclists to gain deeper insights into the perception of this type of separators.

An interesting finding is the difference in preferences of non-cycling males and females. Apparently, it is not a “fear” of cycling due to low-quality infrastructures that deter males from cycling, but it is for women. A policy conclusion of this finding is that improved cycling infrastructure could potentially increase cycling mostly among females than males.

One last point concerns the size of the willingness-to-pay values, which reach the 22-minute mark. In absolute terms, this value is quite high given that the travel times shown to respondents were in average 10.6 minutes. It is unrealistic to think that such a trade-off would occur. Probably, as in fact happens among our respondents, individuals with such high WTP (non-cycling females) actually don't cycle, pointing out that the real trade-off between low-quality cycling infrastructure and good-quality cycling infrastructure occurs at the mode choice and not at the route choice level. For this reason, we focused our interpretation on the relation among the WTP's, rather than on the interpretation of their values. One possible issue, which is hard to verify, is that many respondents did not account for the travel times in their choice decisions, which could be explained by the fact of having these represented only as numbers. The experiment design could be improved in future studies, for example by borrowing the common practice in mode-choice modeling of basing the experiment on revealed-preference data, that is, on previously collected trips. For cyclists, RP data on trips could be collected, and then to pivot the travel times around the travel time of a reported cycling trip.

5 Randomized controlled trial

This section presents the design and results of the randomized controlled trial conducted with the participants from group A in our sample. It is based on Roth et al. (2025).

The transition towards sustainable modes of transport has become a crucial goal for policymakers, given the environmental and economic significance of transportation externalities. In the EU and Switzerland, the monetized external costs amount to approximately 1-2% of GDP (CE Delft, 2019a; Metropia, 2019), and thus form a considerable burden for society. The main externalities in the transport sector are time loss due to congestion, as well as health, accident and climate related external costs and benefits (CE Delft, 2019a). We abstract from road maintenance costs, as these are already internalized via fuel taxes in Switzerland.

Unlike private transportation costs (e.g. fuel costs or public transport tickets), these external costs are mostly ignored in the people's private decision about whether, when, and how to travel from A to B. The presence of external costs results in an inefficient use of the existing transportation infrastructure in the sense of an over-usage in terms of quantity and/or timing. This large-scale market failure presents a valid justification for government action to implement policies which restore the social optimal equilibrium (Eliasson, 2021). Following Pigou (1920) and Vickrey (1969), a tax amounting to the individuals' marginal external damage (Pigovian tax) is the most direct way to internalize these costs and, at least in principle, achieve an efficient outcome.

This chapter extends the literature on applying Pigovian taxation to the transportation sector. We conduct a field experiment to examine how such a tax influences individuals' transport preferences and behaviors. Our sample consists of 1'085 Swiss residents who own an E-bike and regularly drive a car. We focus specifically on an E-bike sample, as E-bikes are presumably a better substitute for cars than conventional bicycles, given that E-bikes are faster and well-suited for longer distances. We employ a randomized controlled trial (RCT) design with a four-week baseline period followed by five weeks after study group assignment. Data on travel behavior and mode choice is gathered by detailed GPS-tracking using a smartphone application (see Chapter 3). The pricing intervention impacts all main transport modes and is adopted by assigning personalized budgets to participants based on their baseline travel needs. External costs are then subtracted from these budgets according to the transportation choices.

Due to the Pigovian marginal external cost pricing scheme, the individuals in our sample reduce their external costs by 6.5%, starting from a baseline daily average of CHF 3.35. This finding confirms the prior result found in Hintermann et al. (2025), who conducted a similar tracking study using a representative car-driving sample in Switzerland. We find that the treatment effect is mainly driven by a reduction in health-related externalities. Regarding the distances traveled, charging the Pigovian tax causes individuals to reduce their daily car distance by 8.2% or 1.94 km, on average. At the same time, bicycle and walking distances increase by 12.6% and 6.1%, respectively, resulting in a significant shift away from driving towards active modes of transport. This effect is more pronounced for individuals who own an

S-pedelec (i.e, an E-bike with support up to 45 km/h) as opposed to a regular E-bike. Mediation analysis shows that people not only reduce the amount of driving but also shift away from congested time windows. Overall, our results suggest that introducing the Pigovian rate reduces the external costs of transport through both mode and peak shifts.

To the extent that our pricing indeed approximates to the true societal costs of transport, this necessarily will translate into a societal net benefit.[4] However, a Pigovian price is rarely implemented. We emphasize that our results also provide insights into the effects of other policy instruments that alter the relative prices of driving, public transport, and cycling. The further a policy instrument deviates from the Pigovian tax, the smaller the societal benefits will be, all else equal.

5.1 Experimental setting

5.1.1 Study design and sample

To estimate the causal effect of charging marginal external costs, we endowed participants with a travel budget based on their baseline needs. The tax, i.e., their calculated external costs, was subsequently deducted from this budget. Participants received weekly mobility reports showing the external costs, the five costliest travels, and the current state of their budget. At the end of the study, they received the remainder on top of the study reward of 50 Swiss Francs (CHF)[5]. The study sample consists of 1'085 E-bike users living in the German- and French-speaking parts of Switzerland. The study used rolling recruitment and lasted from September 15, 2022, to July, 31, 2023. Two waves of participation emerged, with many people starting simultaneously: an initial wave from broad recruitment across multiple channels, followed by a second surge in February after invitations via the Zurich vehicle registration office.[6]

In an initial online survey on travel behavior and demographics, participants were screened and invited into the RCT or another part of the research project that consisted exclusively on observing trips (not shown in Figure 5.1, see Section 3.1). To qualify for the RCT (study group A), respondents had to be at least 18 years old, live in Switzerland, own an E-bike[7], use a car at least twice per week, and not use a regular bicycle.[8]

[4]If we were to choose any arbitrary pricing, we would not know whether the benefits (i.e., the reduction in external costs) outweighs the costs of behavioral adjustment. With the Pigovian rate, however, it must necessarily be the case that society is better off. The welfare computations will be carried out in a future version of Roth et al. (2025).

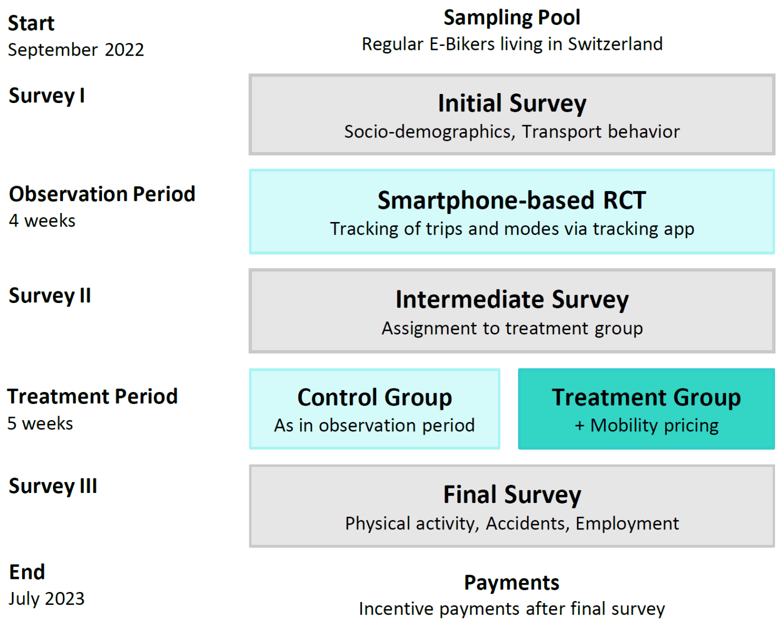
[5]At the beginning of the study, the Swiss Franc was almost exactly at parity with the US dollar.

[6]We will analyze these two waves separately in Section 5.3.3.

[7]In Switzerland, there are two types of E-bikes in use during the study period: “regular” E-bikes (or “pedelecs”) that provide electric support up to 25 km/h, and “S-pedelecs” that assist the user until a speed of 45 km/h. The latter require the use of a helmet and registration as a motor vehicle (in the same category as electric scooters and wheelchairs). Owners of both types of E-bikes were invited into the experiment.

[8]Our app cannot differentiate between bicycles and E-bikes, so in order to be sure that we were observing an E-bike in our data, we chose to limit the sample to people who rarely or never use a regular bicycle. Additionally, individuals were also excluded from the RCT if they were professional drivers (e.g. taxi drivers, bicycle courier, or train drivers), did not own a smartphone, or were not able to walk 200 meters without assistance.

Figure 5.1: RCT study design



Qualifying individuals were then invited to the tracking phase, which started with an observation period during which participants received a weekly summary of their travel behavior (distances and durations per mode) by e-mail. Then, participants were invited to fill out the intermediate survey, in which the treatment was explained and delivered. During the treatment period, participants in the treatment group received an extended weekly report containing information on their external costs. The control group continued just as in the observation period. To receive their incentive payment, participants needed to complete a final survey with questions about their employment, physical activity, and past accidents.

To obtain a sufficient number of E-bike users in a cost-effective manner, we used multiple targeted recruitment channels, as described in Section 3.1. The largest group of participants in the RCT was invited by e-mail via the research institute YouGov[9] (32.3%) and via personalized e-mails to a list of addresses received from the cycling organization Pro Velo[10] (20.6%). Another source were invitations sent by letter via the cantonal vehicle registration offices (18.9%), which have information about owners of S-pedelecs. The remaining individuals were reached via invitations on the intranet of cantonal administrations (3.4%), social media posts on Instagram and Facebook (2.5%), newsletters of cyclist organizations (2.4%), or directly from our website (19.1%)[11]. Section 3.1.1 presents the recruitment strategy of the entire project in more detail.

Table 5.1 summarizes key socio-demographic variables for the introduction survey sample and those that chose to participate in the tracking study. We also show the corresponding variables from the Mobility and Transport Microcensus (MTMC) sample, which is a representa-

[9]Formerly LINK institute, `https://business.yougov.com/`

[10]`https://en.pro-velo.ch/`

[11]The website was linked in the cantonal letters and the social media posts. Unfortunately, we are unable to clearly identify the origin of these entries to the study.

tive survey of Swiss travel habits conducted by the Federal Office of Statistics and the Federal Office of Spatial Development (2023). Comparing the eligible participants ("Intro survey") to the "RCT sample" gives a notion of the selection bias, introduced by not everyone willing to being tracked via a smartphone app. Individuals aged 66 to 87, with a secondary education level, and living in two-person households are less likely to agree to participate in the tracking study. We limit the representative MTMC sample to individuals aged 18 to 87 with access to both a car and an E-bike to ensure a meaningful comparison with our sample. Overall, our recruitment strategy resulted in an RCT sample that closely mirrors the MTMC population in terms of observable characteristics, with some exceptions. For instance, the tracking sample includes fewer young adults (aged 18–30) and fewer females, while participants tend to have higher incomes. Our sample also has a higher share of S-pedelecs due to our recruitment strategy (see above). It shows a similar distribution of mode shares but slightly higher overall travel frequency. Since individuals who regularly use a conventional bicycle were excluded from the RCT, no cycling distance is reported for this sample.

The randomization into treatment and control groups was effective, as indicated by the p-values from two-sample mean tests. Most variables exhibit a balanced distribution across both groups, particularly the pre-treatment averages of the main outcome variables, as shown in the lower part of Table 5.1. However, the treatment group contains a slightly higher proportion of German-speaking individuals. The table also reveals differences in some responses to the income question, though these are based on very few observations, with only 16 individuals reporting an income of less than 4'000 CHF.

5.1.2 The external costs of transport

To compute the marginal external costs of transport, we consider the categories of congestion, climate, health, and accidents. For each category, we focus solely on the external component of these costs, i.e., on the costs (or benefits) that accrue to society at large and are not paid for by the person who makes the transport decision. The most straightforward examples are climate damage and damage from noise and local air pollution, which essentially have no internal component.

Accident-related external costs predominantly consist of the inflicted health costs which are socialized through the insurance system in Switzerland. There is no deductible for accident-related health costs, such that some person A pays for none of the monetary costs out of pocket, rendering them entirely external. Accidents also cause staff shortages and costs for replacing injured or deceased persons. In contrast, damages to vehicles are excluded, as the damage to person B's car caused by person A will be paid either directly by person A or indirectly via a raise in A's personal car insurance premium. Similarly, health costs due to local air pollutants and noise emission are external to traffic participant A. We include these costs separately from the external health benefits of active transport, which are the savings in health care costs due to an increase in physical exercise. We stress that the reduction in mortality due to exercise is not included in our numbers, as this is an internal component (it is the cyclists and walkers themselves who live longer).

Table 5.1: Demographic sample information

Variable	Level	Intro survey	RCT sample			MTMC
			Control	p-value	Treated	
Age	(18 - 30]	2.4	3.1	0.771	3.5	16.7
	(31 - 50]	29.1	42.1	0.957	42.3	34.2
	(51 - 65]	44.2	40.7	0.492	42.8	31.4
	(66 - 87]	24.3	14.0	0.211	11.4	17.7
Education	Mandatory	3.2	2.0	0.485	2.6	7.5
	Secondary	59.9	50.0	0.512	52.0	57.7
	Higher	36.8	48.0	0.327	45.1	34.8
Gender	Female	43.4	41.3	0.121	36.7	50.4
	Male	56.6	58.7	0.121	63.3	49.6
Household size	1	11.3	11.6	0.071	8.3	9.9
	2	49.6	38.6	0.494	36.6	39.4
	3	13.3	16.3	0.663	17.3	18.4
	4	18.9	24.8	0.402	27.0	22.3
	5 or more	7.0	8.7	0.245	10.7	9.9
Monthly household income	4'000 CHF or less	3.4	2.4	0.028*	0.7	5.3
	4'000 CHF - 8'000 CHF	26.6	22.4	0.864	22.9	24.7
	8'000 - 12'000 CHF	23.9	25.6	0.12	29.8	25.6
	12'000 - 16'000 CHF	24.2	30.7	0.056	25.5	13.8
	16'000 CHF or more	12.3	14.2	0.114	17.7	11.6
	Prefer not to say	8.3	4.5	0.04*	2.3	8.3
	I don't know	1.3	0.2	0.041*	1.2	10.6
Language	German	85.4	81.9	0.039*	86.5	78.7
	French	12.0	14.4	0.073	10.7	18.0
	Italian					3.3
	English	2.6	3.7	0.372	2.8	
Nationality	Swiss	86.5	82.7	0.445	84.4	86.0
	Other	13.5	17.3	0.445	15.6	14.0
Residential setting	Rural	15.6	12.2	0.417	13.9	20.4
	Periurban	28.5	27.2	0.885	27.6	26.1
	Urban	55.9	60.6	0.492	58.6	53.6
Access to car	Yes	96.6	95.3	0.653	95.8	72.2
	Sometimes	3.4	4.7	0.653	4.2	22.7
	No		0.0		0.0	5.2
E-bike (25 km/h) ownership	Yes	63.9	59.6	0.596	58.1	89.5
E-bike (45 km/h) ownership	Yes	44.0	49.0	0.419	51.5	14.8
Full public transport subscription	Yes	6.4	7.7	0.487	8.8	14.3
Half fare public transport subscription	Yes	66.8	69.9	0.814	70.5	45.6
Distance	Car distance (km)		28.4	0.068	26.3	26.7
	PT distance (km)		9.1	0.226	10.2	6.7
	E-bike distance (km)		5.1	0.591	4.9	0.9
	Bicycle distance (km)					0.9
	Walking distance (km)		1.8	0.154	1.9	1.5
	Total distance (km)		44.7	0.412	43.6	40.2
Duration	Total duration (min)		92.1	0.774	91.5	84.2
External costs	Climate ext. costs (CHF)		1.1	0.136	1.1	
	Congestion ext. costs (CHF)		0.7	0.207	0.7	
	Health ext. benefits (CHF)		-1.1	0.853	-1.1	
	Health ext. costs (CHF)		1.2	0.264	1.2	
	Accident ext. costs (CHF)		1.5	0.305	1.4	
	Total ext. costs (CHF)		3.5	0.157	3.3	
Private costs	Private costs (CHF)		10.4	0.509	10.2	
Recruitment wave	Autumn	74.6	71.7	0.657	72.9	
N		5'993	508		577	11'176

Notes: Descriptive statistics for all individuals eligible for the study, the RCT study sample, and the comparable weighted sample from the Swiss Mobility and Transport Microcensus 2021 (MTMC), including households with at least one E-bike and one car. The first panel presents percentages, while the bottom panel shows baseline averages with units given in parentheses. * p-value $<$ 0.05 indicates significant differences between the control and treatment groups, without correction for multiple hypothesis testing.

This approach and the corresponding external costs are based on official values published by the Swiss Federal Office for Spatial Development in 2021 (Metropia, 2019). However, this report lacks indications for electric cars and E-bikes. We therefore estimated these values based on their non-electric counterparts and the emission factors for electricity production in Switzerland (Sacchi and Bauer, 2023b). Furthermore, we adjusted the accident-related external costs for E-biking such that they exactly offset the external benefits, resulting in net zero external costs for this mode.[12] In a recent update of the external costs calculations, the Federal Office for Spatial Development now estimates an external benefit of 2.1 cents per km for E-bikes (Ecoplan-INFRAS, 2024), which is very close to the adjusted rate calculated for this study.

Table 5.2: Marginal external costs by mode

		Car	E-Car	Motorcycle	E-Bike	Walking	Bus	Tram	Train
Climate & environment	Climate	1.52	0.09	1.05	-	-	0.76	-	0.01
	Nature and landscape	0.87	0.68	0.48	0.50	0.36	0.26	0.03	0.47
	(Toxic-) ground poll.	0.08	0.08	0.05	-	-	0.16	-	0.12
	Up-/downstream proc.	0.86	0.46	0.76	1.36	-	0.46	0.66	0.17
	Urbanisation/separation	0.22	0.22	0.16	-	-	0.17	0.13	0.15
	Total	3.55	1.52	2.51	1.86	0.36	1.81	0.82	0.92
Accidents		2.15	2.15	14.32	12.85	7.97	2.70	1.34	0.16
Health benefits		-	-	-	-14.72	-18.30	-	-	-
Health costs	Local pollutants	2.57	1.93	0.69	-	-	-	-	1.42
	Noise	1.04	0.78	14.77	-	-	1.01	0.15	0.86
	Total	3.61	2.71	15.46	-	-	1.01	0.15	2.29
Congestion	Average†	2.65	2.67	0.66	-	-	-	-	-
Total		**11.96**	**9.05**	**32.95**	**0.00**	**-9.97**	**5.51**	**2.31**	**3.37**

Note: Values in Swiss cents per person-kilometer, based on Metropia (2019) and own calculations for E-cars and E-bikes. † The congestion values are observed averages in the data (see below for congestion costs). For many trips, the congestion externality is zero.

The resulting values are shown in Table 5.2. For public transport, walking, and E-biking, the external costs are constant per kilometer, as differences across time and space are not considered. For walking, the health benefits outweigh the accident costs, such that this mode exhibits net external benefits.

For cars and motorcycles, the external costs consist of a fixed per-km rate (which differs between regular and electric cars), and a time- and location-specific component for the external cost of congestion. However, providing the experiment participants with a continuous menu of prices is not ideal. To simplify the price schedule and thus increase its salience, we discretize the continuous distribution of congestion costs by computing the average congestion externality for three urbanization levels and four different time periods per day. This approach is based

[12]This reduction was implemented because of the difficulty conveying positive net external costs of cycling to E-bikers. To achieve a net zero value, the external accident costs provided by the Swiss Federal Government have to be cut in half. This reduction leads to external cost numbers that are very close to those reported for the Netherlands or Denmark (Castro et al., 2018a). These countries have lower bicycle-related accidents (per km) due to a better infrastructure and a higher bicycle mode share, leading to "safety in numbers". In this sense, our numbers reflect a future in which cycling in Switzerland is similar in terms of safety to cycling in these countries.

on the external congestion costs observed in Hintermann et al. (2025) that were estimated using the approach described in Molloy et al. (2021b). The degree of urbanization of origin and destination points are taken from the official categorization of the Eurostat (2021). The classification includes 1 for dense urban areas, 2 for medium-density areas, and 3 for sparsely populated areas. As shown in Table 5.3, the highest congestion costs occur during the evening peak within urban areas.

Table 5.3: Congestion costs of car travel for different times and regions

Trip Direction: (origin→destination)	**1→1**	**1→2**	**1→3**	**2→1**	**2→2**	**2→3**	**3→1**	**3→2**	**3→3**
Morning Rush-Hour 6:30-8:30	7.0	2.5	1.9	4.5	2.0	1.3	3.0	1.1	0.6
Off-peak Hours 8:30-16:30 & 18:30-20:00	5.7	3.3	2.4	3.0	1.9	1.0	2.1	1.1	0.5
Evening Rush-Hour 16:30-18:30	10.3	6.7	4.2	5.2	3.2	1.7	2.9	1.7	1.2
Night 20:00-6:30	0	0	0	0	0	0	0	0	0

Note: Congestion costs denoted in cents/km. 1: Dense urban area (cities), 2: Medium density area (towns and suburbs), 3: Sparsely populated areas (rural areas). Reading example: A trip from an urban area (1) to a medium density area (2) during evening rush hour is assigned an external congestion cost of 6.7 cents per km.

5.1.3 Treatment

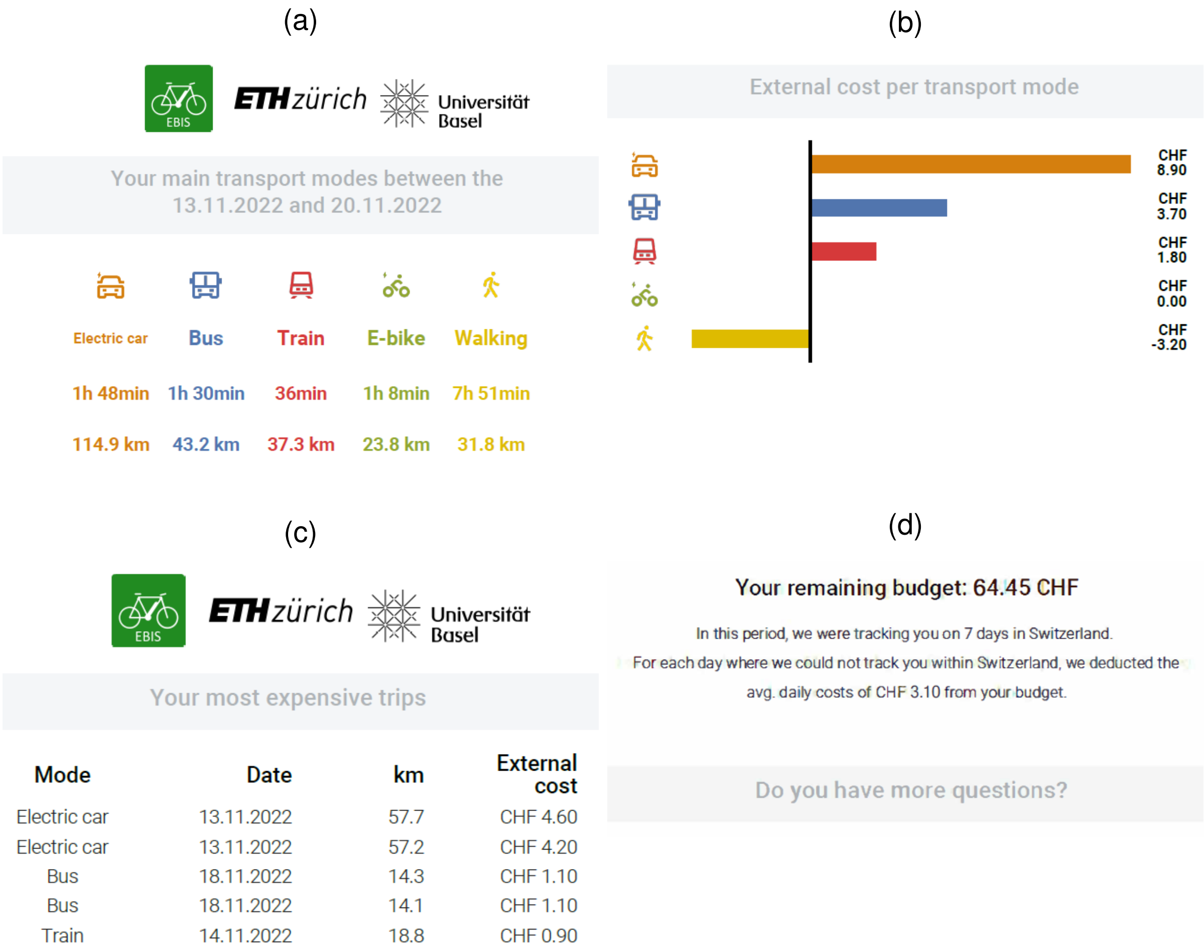
During the four-week observation period, the participants were presented with a weekly summary of their travel behavior, including duration and distance by mode of transport (Figure 5.2a). Upon invitation to the intermediate survey, the participants were randomly assigned to the treatment or control group.[13] In this survey, we explained the concept of external costs of transport to the participants assigned to the treatment group, along with a simple graphic showing the external cost rates per mode. We informed the participants that their allocated budget would be used to cover the external costs generated by their travel, and that any remaining funds in their account at the conclusion of the study would be retained by them. To make sure everyone understood the setup, we included two comprehension questions on external costs and the possibility to earn money by reducing their externalities. Participants who answered the question incorrectly were presented with the same information again. Upon completing the intermediate survey, all information was emailed to the participants, including a personalized graph of the summed external costs by mode of the baseline period for the person in question, and links to a basic as well as a detailed explanatory document (only the latter included Table 5.3 to explain the congestion costs in detail).

The budget was personalized based on participants' individual average daily external costs produced during the observation period, supplemented with an additional 20% buffer. This

[13]We restrained from stratifying the randomization due to the technically challenging implementation in a setup with rolling admission.

buffer was included to reduce the likelihood that participants would exhaust their budget due to price-unrelated shocks during the observation or treatment period, e.g. in the form of mean reversion.

Figure 5.2: Example of a weekly report



Throughout the duration of the treatment period, participants in the treatment group were provided with weekly summaries sent by e-mail enabling them to track their external costs (and thus their payments). The costs were presented according to the specific mode of transportation used (Fig. 5.2b). An individual list of the costliest trips of the last week was presented (Fig. 5.2c), while the remaining budget as well as the amount of valid tracking days were also reported (Fig. 5.2d). Person-days with tracking information of less than 10 hours in Switzerland (stays and travel together) were defined as missing; for these days, we deducted the personal average external costs of the observation period (see Fig. 5.2d) in order to reduce the potential of gaming the experiment by simply switching off the app, and to base our analysis only on sufficiently tracked days. Section A.1.2 provides further robustness checks for the existence of strategic behavior in connection with the tracking app.

The control group continued to receive the information in Figure 5.2a in their weekly mobility reports during the entire experiment. To reduce the threat of differential attrition, the control group was shown a graph summarizing the kilometer distances per mode of the entire baseline period in the intermediate survey.

5.2 Empirical framework

This section describes our handling of the data and the empirical strategy for measuring the impact of the treatment.

Data preparation For the empirical analysis, we aggregate the data from the observed stage level to the person-day level. Thus, we analyse external costs and distances per person and day, by mode and over all modes combined. To ensure the validity and accuracy of our results, we implemented a data cleaning process. It involved removing any implausible or obviously erroneous observations, which we believe to be primarily a result of measurement errors by the app. Hence, we remove data points if the following conditions applied: Average daily speed exceeds 100 km/h for car, motorbike, and public transport, 50 km/h for cycling, or 20 km/h for walking; total distance traveled exceeds 500 km/day for car, motorcycle, and public transport, 100 km/day for cycling, or 20 km/day for walking. Whenever any of these conditions was met, we removed the involved person-day from the analysis. To limit the reliance on only partially tracked days and ensure the study's locational coherence, we only consider days with more than 10 hours of tracking within Switzerland.[14] For the analysis, we only included participants that delivered at least eight valid tracking days in the baseline period. Since not all individuals completed the intermediate survey immediately after being invited, some participants remained in the study for more than 70 days.

In case of travel demand shocks in any of the two periods, participants may have exhausted their travel budget. Despite the 20% buffer added, 15.6% of the individuals depleted their budget before the end of the study. In such cases, we informed participants that their travel budget would be increased once more, scaled again according to their baseline travel needs. The e-mail notifying participants of the unannounced increase clearly stated that this adjustment would only occur once to preserve the integrity of the incentive structure. However, 30 participants depleted their budget twice. These days with a negative travel budget are included in regressions with a fixed effect to account for potential distortion from ineffective incentives.[15]

Regression analysis The randomized treatment yields an exogenous variation that can be directly used to identify causal treatment effects. The average treatment effect (ATE) is estimated by comparing means between treated and control observations using the following difference-in-differences (DiD) regression framework:

[14] For days that fulfilled this condition we included all recorded travel, viz., we included trips outside of Switzerland, which were also priced with the Swiss external cost rates.

[15] Omitting these 249 days from the regression would introduce systematic differential attrition across treatment groups. By using a fixed effect for these days, we avoid this issue, which is conceptually equivalent to introducing a dummy variable to control for their occurrence.

$$Y_{it} = c_0 + \tau \cdot DiD_{it} + \sum_{k=1}^{K} \beta_k \cdot x_{ik} \cdot DiD_{it} + \mu_i + \mu_t + \epsilon_{it} \tag{5.1}$$

The dependent variable is the outcome of interest for person $i \in (1, ..., N)$ on calendar day $t \in (1, ..., T)$. The main outcomes of interest are external costs (in CHF per day) and the distances by mode. The difference-in-differences term, DiD, is the product of a treatment group dummy (D_i) and a treatment period dummy (D_t). It equals one if the treatment is active for person i on a given day t, and zero otherwise. The ATE is given by the coefficient estimate $\hat{\tau}$. Due to rolling recruitment, the first day of the treatment falls on different calendar days for different people.

To account for unobserved common shocks, we include individual-specific (μ_i) and date-specific (μ_t) fixed effects. The error term ϵ_{it} has an expected mean of zero and a variance of σ^2. We allow for correlation of the error within, but not across participants.[16]

To examine potential treatment effect heterogeneity (known as effect *moderation*), we include a k-dimensional vector of socio-demographic variables x and interact it with the treatment indicator. This allows us to examine, for instance, whether men respond more strongly to monetary incentives than women or whether income moderates the effect.

We are most interested in proportional effects to account for the fact that some people travel much more than others in absolute terms. This can be directly implemented by estimating Equation 5.1 using a Poisson Pseudo-Maximum Likelihood (PPML) model.[17] However, for the regressions that focus on total external costs, this approach would result in dropping all person-days that exhibit negative total external costs due to walking. To avoid this problem, we estimate these regressions in levels and then compute the proportional responses by dividing the coefficients (in CHF/d) by the potential average daily external costs of the treated group had they not been treated. This unobserved outcome is estimated by applying the same percentage change observed in the control averages to the treated pre-treatment average total external costs, thus following the spirit of the common trends assumption.

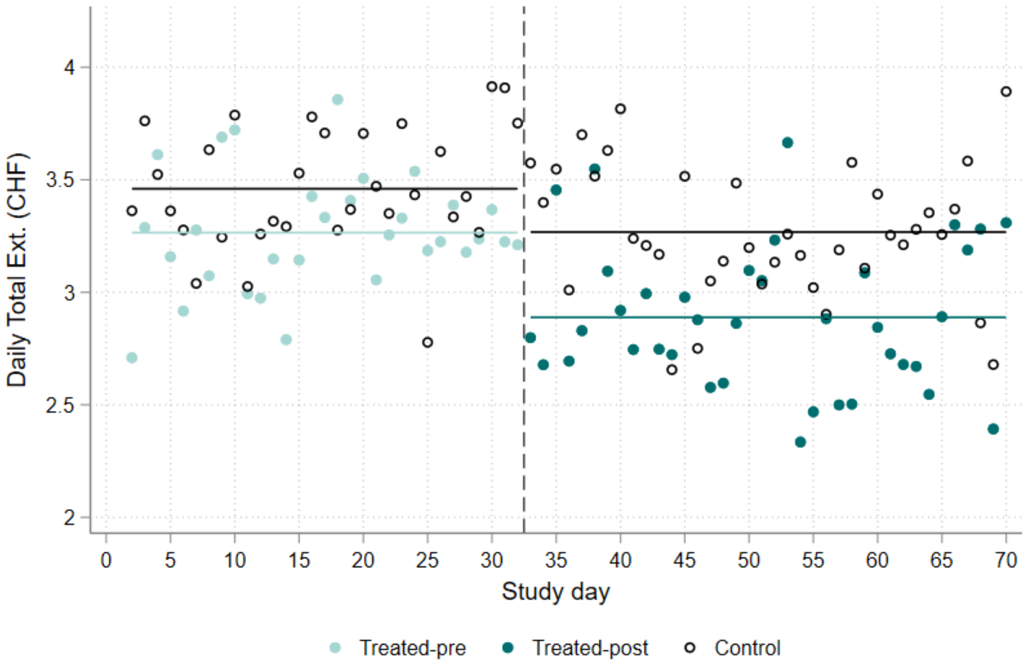
Thanks to the randomization of the treatment assignment, our setting is expected to satisfy the assumptions required for the causal identification of the ATE using the difference-in-differences estimator. Table 5.1 supports the comparability of the two study groups (and thus unconfounded assignment). Table A.1 and Table A.2 in the appendix provide an indication that the common trends hypothesis holds for distances and external costs during the observation period (and thus expectedly also during treatment, where it cannot be tested). The same anal-

[16]Our identification strategy touches on a recent literature that discusses the validity of the two-way fixed effects estimator in the context of “staggered” DiD designs(Callaway and Sant’Anna, 2021; de Chaisemartin and D’Haultfœuille, 2022; Sun and Abraham, 2021). However, in our setting, with rolling study participation and a large share of never-treated units, bad comparisons (i.e., late vs. early-treated) are of limited concern. Nevertheless, because the study spanned multiple seasons, used different recruitment channels and is subject to self-selection, it may be subject to dynamic treatment effects. To alleviate concerns in that regard, we confirm our results by applying the estimator suggested by Sun and Abraham (2021), which replicates our results almost exactly.

[17]We prefer this specification over the log-linear model because it easily accommodates days with zero travel and mitigates potential bias from heteroskedasticity that can arise in the log-linear framework (see Santos Silva and Tenreyro, 2006).

ysis also provides supporting evidence for the assumption of the treated not anticipating the treatment. Lastly, the identification of our treatment effects hinges on the Stable Unit Treatment Value Assumption (SUTVA), which states that there are no spillovers from the treated on the control group. Given that the participants self-selected into the study, this assumption is threatened, should a treated and a control group person know each other. To alleviate this issue, the treatment assignment process was adapted such that individuals at the same home address were assigned to the same group.

Figure 5.3: Illustration of DiD identification approach



Note: The dots represent average total external costs per study day over all participants in the respective treatment group. The horizontal lines show the average across these points for the entire period (pre- and post-treatment). The data are based on the measured external costs, without deducting the fixed effects. The vertical dashed line only serves an illustrative purpose, because not all individuals enter the second period on the same study day.

The seasonal variation in travel distance by mode presented in Figure 3.11a also impacts the external costs of transport. The described DiD approach, which includes a never-treated control group, allows to absorb these seasonal trends and to identify the within-person variation, which is of primary interest. Figure 5.3 illustrates this idea using the the total external costs of transport. The dots represent the average external costs per study group, aggregated to the daily level. The dashed line marks the day on which the participants filled in the intermediate survey and were are assigned to the treatment or control group.[18] The horizontal lines reflect the average levels of external costs for the entire period per group. Using DiD with individual- and date-specific fixed effects is equivalent to comparing the differences in these lines per group, after subtracting individual- and date-specific fixed effects from the outcome

[18]Note that not all individuals filled in the intermediate survey on the day on which they were invited to do so.

variable of interest. The common trend assumption states that the difference between the two black lines for the control group would also be the difference for the treated group, in the absence of the treatment. Thus, the larger difference in the "treated" lines minus the difference in the black lines is the estimated average treatment effect (ATE).

5.3 Results

5.3.1 Descriptive statistics

Table 5.4 provides an overview of the tracking data during the baseline period for the full sample. These numbers provide key statistics on the Swiss E-bike population and describe their travel behavior. The table aggregates data from Table 5.1 and presents averages at the participant-day level. Introducing a tax on the external costs of transport increases total marginal transport costs by about one-third. Of the tracked stages, 87% were confirmed by app users, while 6.5% were corrected. On average, we recorded 25 valid tracking days per person, covering 44 km and 92 minutes of travel per day.

Table 5.4: Summary of the tracking data in the baseline period

Variable	Average	Std. Dev.	Unit
Climate ext. costs	1.10	1.60	CHF/day
Congestion ext. costs	0.67	1.36	CHF/day
Health ext. benefits	-1.08	1.58	CHF/day
Health ext. costs	1.20	1.98	CHF/day
Accident ext. costs	1.46	1.74	CHF/day
Total ext. costs	**3.35**	**5.79**	**CHF/day**
Private costs	**10.20**	**16.40**	**CHF/day**
Car distance	27.06	47.44	km/day
Public transport distance	9.72	35.22	km/day
E-Bike distance	4.95	10.64	km/day
Walking distance	1.91	2.53	km/day
Total distance	**43.95**	**56.49**	**km/day**
Total duration	**92.16**	**84.42**	**min/day**
Total stages	7.22	5.02	#/day
Confirmed	87.06	32.73	%
Corrected	6.53	15.78	%
Valid tracking days	25.07	4.98	days

Note: Average and standard deviation calculations based on 27'196 recorded days during the baseline period.

The corresponding averages in the car-focused sample from Hintermann et al. (2025) are approximately 4.60 CHF/day in total external costs, 22.70 CHF/day in private costs, and an average daily distance of 48 km. Despite these differences, likely due to higher car usage, the total time spent traveling per day is nearly identical (93 minutes).

5.3.2 Average treatment effects

Based on the regression formula in subsection 5.2, the average treatment effect (ATE) is given by the estimate for τ in eq. (5.1). Table 5.5 shows the ATE in absolute and relative terms. Column (1) shows the effect on total external costs. Introducing a Pigou-inspired tax reduces external costs by 0.213 CHF,[19] or 6.9% on average. The remaining columns report results

Table 5.5: Average treatment effect on external costs

	(1) Total costs	(2) Climate	(3) Congestion	(4) Health benefits	(5) Health costs	(6) Accidents
ATE (CHF)	-0.213*	-0.049*	-0.068***	0.106***	-0.043	0.053
	(0.091)	(0.025)	(0.020)	(0.026)	(0.032)	(0.029)
adj. R^2	0.116	0.127	0.114	0.323	0.115	0.221
ATE (relative)	-0.069*	-0.050*	-0.116***	0.106***	-0.043	0.038
	(0.029)	(0.023)	(0.031)	(0.024)	(0.028)	(0.020)
Pseudo R^2	-	0.103	0.130	0.219	0.114	0.130
Clusters	1'085	1'085	1'085	1'085	1'085	1'085
N	61'410	61'410	61'410	61'410	61'410	61'410

Notes: * $p<0.05$, ** $p<0.01$, *** $p<0.001$. Standard errors (in parentheses) are clustered at the participant level. For total external costs, relative effects were calculated by dividing the ATE (in CHF) by the average of the control group during the treatment phase, using a bootstrap with 1'000 draws. For (2)-(6), relative effects are calculated using a PPML regression. All regressions include person and date fixed effects, as well as a dummy variable indicating days following the receipt of a negative travel budget in the mobility report.

per cost dimension and show that the largest effect consists in an increase in external health benefits. Accident-related externalities are not significantly reduced due to the substantial accident risk associated with E-biking. The relative reduction in total external costs implies an elasticity of 0.217 (s.e. 0.091) with respect to the average price increase of 31.6% due to the tax.[20]

Table 5.6 presents the ATEs on daily distances (measured in km), in total, and separately by mode. The price intervention has no significant effect on the total distance traveled. However, it leads participants to reduce their driving distance by 8.2% on average, while increasing the distance traveled by public transport, E-bike, and walking.

Figure 5.4 graphically illustrates the relative ATE by mode for both groups of outcome variables. It suggests that the overall decrease in total external costs is largely due to mode shift away from driving towards the other modes of transport.

Figure 5.4a shows that the overall decrease in total external costs is largely due to the decrease in car distance and, thus, car-related externalities. This reduction of car kilometers together with an increase in bicycling and walking, as well as public transport, explains the

[19]This coefficient was confirmed using the estimator by Sun and Abraham (2021), which results in a total effect of -0.207 CHF with a standard error of 0.088, and a p-value of 0.019, when grouping individuals according to the 106 unique dates when they entered the treatment phase.

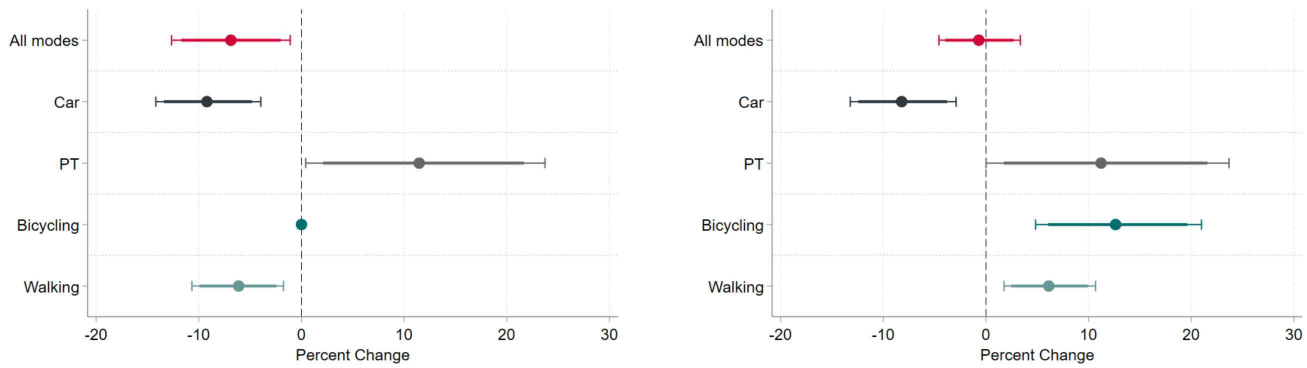
[20]The corresponding standard errors are derived from a bootstrapping procedure with 1,000 draws.

Table 5.6: ATE on travel distance

	(1) Total distance	(2) Car	(3) Public transport	(4) E-Bike	(5) Walking
ATE (km)	-0.248	-1.935**	0.949	0.570**	0.118**
	(0.861)	(0.733)	(0.529)	(0.179)	(0.042)
adj. R^2	0.125	0.124	0.136	0.319	0.203
ATE (relative)	-0.007	-0.082**	0.112*	0.126**	0.061**
	(0.020)	(0.029)	(0.054)	(0.037)	(0.021)
Pseudo R^2	0.176	0.193	0.321	0.428	0.146
Clusters	1'085	1'085	1'085	1'085	1'085
N	61'410	61'410	61'410	61'410	61'410

Notes: * $p<0.05$, ** $p<0.01$, *** $p<0.001$. The dependent variable contains the distance traveled including zeroes aggregated to the person-day level. The ATE (km) coefficients show the ATE in kilometers. The relative coefficients were estimated using a PPML model. Standard errors (in parentheses) are clustered at the participant level. All regressions include person and date fixed effects, as well as a dummy variable indicating days following the receipt of a negative travel budget in the mobility report.

Figure 5.4: ATE on external costs and distances



(a) External costs (b) Travel distance

Notes: Graphical representation of the regression results in Table 5.5 and Table 5.6. The thick bars represent 90% confidence intervals, while the thin bars indicate 95% confidence intervals. Note that walking generates net benefits (i.e., negative external costs), while external costs associated with E-biking are set to zero.

reduction in external costs. Importantly, Figure 5.4b indicates a direct shift from car to modes with less emissions because our treatment did not affect the overall average distance traveled per day. Charging the external costs of transport does not limit overall travel, but leads to a re-optimization of the mode choices, now considering all effects related to that choice.

5.3.3 Effect heterogeneity

So far, we have focused on the average treatment effect and the underlying mechanisms. Next, we examine effect moderation, i.e., how the effect varies with pre-treatment characteristics contained in the vector x in eq. (5.1) and over time.

Fast vs. regular E-bikes Table 5.7 indicates that the distance effect is primarily (though not exclusively) driven by S-pedelec owners. In contrast, the effect for regular E-bike owners (captured by the coefficient on *Treated*) is considerably smaller and statistically significant only for distances covered by public transport and on foot.

Table 5.7: Fast vs. slow E-bikes

	(1) Total distance	(2) Car	(3) Public transport	(4) E-Bike	(5) Walking
Treated	0.020	-0.049	0.169*	0.036	0.080**
	(0.027)	(0.036)	(0.071)	(0.053)	(0.027)
Treated x Owns S-pedelec	-0.049	-0.067	-0.090	0.130*	-0.033
	(0.034)	(0.047)	(0.088)	(0.056)	(0.035)
Pseudo R^2	0.176	0.193	0.321	0.429	0.146
Clusters	1’085	1’085	1’085	1’085	1’085
N	61’410	61’410	61’410	61’410	61’410

Notes: * p<0.05, ** p<0.01, *** p<0.001. The coefficients were estimated using a PPML model, and the results show proportional effects. Standard errors (in parentheses) are clustered at the participant level. All regressions include person and date fixed effects, as well as a dummy variable indicating days following the receipt of a negative travel budget in the mobility report.

Pre-treatment transport behavior Table 5.8 presents the results from including interaction terms for pre-treatment distance shares of E-bikes and cars. The coefficient on *Treated* captures the treatment effect for those who had a prior E-bike or car share of zero. In the first part of Table 5.8, the significant and positive coefficients for these reference groups in columns (1)-(3) indicate that the relative increase in bicycle distance is strongest for individuals with an initially very low bicycle share, and decreases with the baseline share of this mode. Intuitively, people who already carry out most of their trips by bicycle cannot respond much to the pricing, whereas those that rarely use their E-bike can (and do) more easily increase usage in response to the treatment. Column (4) confirms that those with a lower pre-treatment E-bike share also reduce their car kilometers by more. Finally, columns (5) and (6) indicate that the shift away from driving is more pronounced for frequent drivers.

In the second part of Table 5.8, we estimate the effect in absolute terms (in kilometers) to address the concern that these results could be driven by similar absolute increases, which translate into much larger proportional changes for individuals with low pre-treatment mode shares. However, the absolute results confirm the pattern observed in the proportional ones: respondents with low baseline cycling shares exhibit significantly larger absolute increases than those with higher baseline shares. Similarly, columns (4)-(6) confirm that the reduction in absolute driving is larger for frequent drivers and for those that do not use their bicycle much during the pre-treatment period. Taken together, these results indicate that the mode shift is due to regular drivers driving less and infrequent cyclists cycling more.

Table 5.8: ATE on travel distance with pre-treatment mode share interaction

	(1) E-Bike	(2) E-Bike	(3) E-Bike	(4) Car	(5) Car	(6) Car
Relative						
Treated	0.365***	0.002	0.414*	-0.125***	0.133	0.157
	(0.077)	(0.068)	(0.146)	(0.035)	(0.067)	(0.101)
Treated x E-Bike share (pre)	-0.393**		-0.413**	0.314*		-0.041
	(0.162)		(0.204)	(0.137)		(0.179)
Treated x Car share (pre)		0.359	-0.054		-0.302***	-0.317**
		(0.171)	(0.214)		(0.097)	(0.126)
Pseudo R^2	0.429	0.429	0.429	0.193	0.193	0.193
Absolute (km)						
Treated	1.453***	-0.411	1.545***	-3.962***	4.586***	4.826**
	(0.203)	(0.331)	(0.444)	(0.960)	(1.189)	(1.788)
Treated x E-Bike share (pre)	-3.972***		-4.072***	9.122***		-0.499
	(0.744)		(0.916)	(2.693)		(3.191)
Treated x Car share (pre)		2.006***	-0.142		-13.326***	-13.590***
		(0.518)	(0.608)		(2.213)	(2.636)
adj. R^2	0.320	0.319	0.320	0.124	0.124	0.124
Clusters	1’085	1’085	1’085	1’085	1’085	1’085
N	61’410	61’410	61’410	61’410	61’410	61’410

Notes: * $p<0.05$, ** $p<0.01$, *** $p<0.001$. The dependent variable contains the distance traveled including zeroes aggregated to the person-day level. The E-bike and car shares are pre-treatment average km-shares over all person-days. The relative coefficients were estimated using a PPML model, and the results show proportional effects. Standard errors (in parentheses) are clustered at the participant level. All regressions include person and date fixed effects, as well as a dummy variable indicating days following the receipt of a negative travel budget in the mobility report.

Socio-demographic subgroups To examine effect heterogeneity with respect to socio-demographic characteristics, we engage in a multivariate analysis including several interaction terms. The interaction terms are chosen based on key socio-demographic variables identified as primary determinants of travel behavior in Hintermann et al. (2025). As shown in Table 5.9, the only significant interaction terms relate to E-bike distances. Column (4) indicates that individuals living in urban areas increase their bicycle distance significantly more, by 15.4%, compared to those in rural areas. Furthermore, individuals using faster E-bikes, such as S-pedelecs, increase their cycling distances by 17.7% more compared to those using standard (slower) E-bikes. We do not find evidence of effect heterogeneity with respect to the other modes.

We also conduct multivariate interactions for all types of external costs (see Table A.7 in the appendix). Most of the interaction terms are insignificant at conventional levels. The only exceptions are that people living in urban areas increase health benefits by 9% more (which is consistent with the result on E-bike distances) and that people above age 50 reduce accident-related external costs by 6.9% more than people below this age.

Table 5.9: Multivariate interactions: Distances

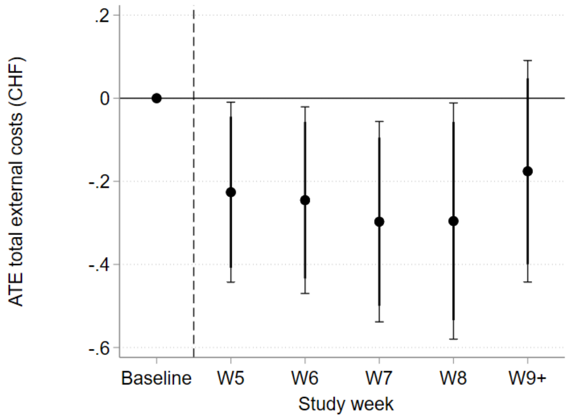
	(1) Total distance	(2) Car	(3) Public transport	(4) E-Bike	(5) Walking
Treated	0.081	0.025	0.521	0.029	0.094
	(0.060)	(0.078)	(0.234)	(0.139)	(0.065)
Treated x Male=1	-0.060	-0.021	-0.164	-0.062	0.004
	(0.033)	(0.046)	(0.092)	(0.064)	(0.034)
Treated x Age>=50	-0.047	-0.066	-0.014	-0.033	-0.029
	(0.035)	(0.050)	(0.094)	(0.065)	(0.036)
Treated x Tertiary educ.=1	0.006	0.012	0.009	-0.026	0.010
	(0.036)	(0.049)	(0.118)	(0.067)	(0.039)
Treated x HH size<3	-0.015	-0.015	-0.028	0.013	-0.032
	(0.035)	(0.050)	(0.092)	(0.068)	(0.037)
Treated x French=1	0.012	0.041	-0.074	-0.061	-0.037
	(0.048)	(0.067)	(0.132)	(0.085)	(0.049)
Treated x Urban=1	-0.007	-0.053	0.067	0.154*	-0.006
	(0.031)	(0.045)	(0.082)	(0.062)	(0.035)
Treated x PT reduction=1	0.012	-0.000	-0.169	-0.019	0.028
	(0.040)	(0.052)	(0.176)	(0.077)	(0.048)
Treated x S-pedelec (max. 45 km/h)=1	-0.036	-0.066	-0.069	0.177**	-0.042
	(0.035)	(0.049)	(0.095)	(0.060)	(0.037)
Pseudo R^2	0.176	0.193	0.321	0.429	0.146
Clusters	1'085	1'085	1'085	1'085	1'085
N	61'410	61'410	61'410	61'410	61'410

Notes: * p<0.05, ** p<0.01, *** p<0.001. The dependent variable contains the distance traveled restricted to positive observations aggregated to the person-day level. All dimensions include one omitted category. *Treated* is thus associated with an observation that has a zero for all included dummies. The coefficients were estimated using a PPML model, and the results show proportional effects. Standard errors (in parentheses) are clustered at the participant level. All regressions include person and date fixed effects, as well as a dummy variable indicating days following the receipt of a negative travel budget in the mobility report.

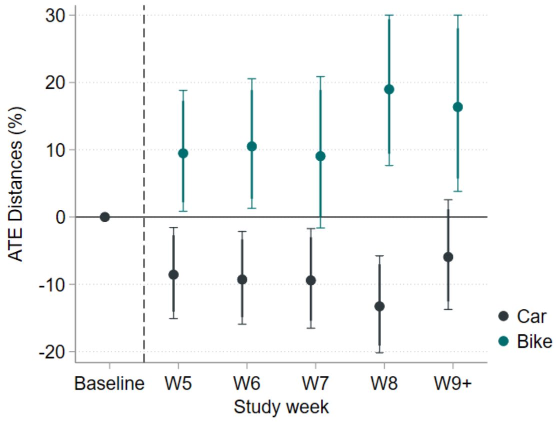
Variation over time Figure 5.5 presents DiD regression results with separate treatment dummies for each study week. This enables us to estimate separate treatment effects for each of the five weeks in the post-treatment phase, relative to the pre-treatment average. While there is some variation in the point estimates for both external costs and distances, these are not statistically different from one another, meaning we cannot reject the null hypothesis of an immediate and constant treatment effect.

The EBIS study spanned multiple seasons. Table 5.10 presents the treatment effects separately for individuals who started the RCT in autumn versus those who started in spring.

Figure 5.5: Treatment effect dynamics



(a) External costs (CHF)



(b) Travel distance (%)

Notes: Both figures display results from a DiD-type regression in which the treatment dummy is replaced by an interaction between each post-treatment study week and the treated group. This approach is related to the event study design but differs in that all baseline period weeks are used as a control group to increase statistical power. All regressions include person and date fixed effects. The thick bars represent 90% confidence intervals, while the thin bars indicate 95% confidence intervals.

The total effect in the autumn wave is captured by the coefficient on *Treated*, whereas the total effect for the spring wave is listed below. Table 5.10 shows that the observed effects are mostly driven by participants in the autumn wave, as none of the treatment effects in the spring wave are statistically significant, even though most point estimates have the expected sign (except for walking, which shows an effect close to zero). Given our data and recruitment strategy, we cannot determine whether the effect is genuinely absent in spring or whether participants recruited during this period, who were mostly from Zurich canton and primarily owners of fast E-bikes, are simply less price-responsive than earlier recruits. Additionally, since the spring treatment group consisted of only 157 individuals (compared to 420 in the autumn wave), the lack of significant effects may also be due to insufficient statistical power in the second wave.

5.3.4 Mechanisms

To identify the mechanisms that give rise to the treatment effect, we engage in a mediation analysis using the methodology developed by Baron and Kenny (1986), Kraemer et al. (2008), and Imai et al. (2010).

Given that a substantial part of the treatment effect seems to arise from a decrease in driving (see Figure 5.4), our candidate for the role of main mediator is car distance. We thus regress car distance on the treatment effect (to measure the effect of the treatment on driving) and include car distance as a control variable in a second regression in which we regress total external costs on the treatment indicator; we also include an interaction term between the treatment indicator and the mediator to account for the possibility that the relationship between the treatment and the outcome variable differs with the amount of driving.

Table 5.11 presents the estimates for the Average Direct Effect (ADE) as well as the Av-

Table 5.10: Seasonality of the treatment effects

	(1) Total distance	(2) Car	(3) Public transport	(4) E-Bike	(5) Walking
Treated	-0.011	-0.103**	0.157*	0.146**	0.090***
	(0.025)	(0.034)	(0.064)	(0.043)	(0.025)
Treated x Spring	0.015	0.089	-0.129	-0.048	-0.088
	(0.044)	(0.064)	(0.121)	(0.079)	(0.049)
Treated + Treated x Spring	0.004	-0.023	0.008	0.087	-0.007
	(0.036)	(0.054)	(0.102)	(0.066)	(0.042)
Pseudo R^2	0.176	0.193	0.321	0.428	0.146
Clusters	1’085	1’085	1’085	1’085	1’085
N	61’410	61’410	61’410	61’410	61’410

Notes: * p<0.05, ** p<0.01, *** p<0.001. The dependent variable contains the distance traveled including zeroes aggregated to the person-day level. The coefficients were estimated using a PPML model, and the results show proportional effects. Standard errors (in parentheses) are clustered at the participant level. All regressions include person and date fixed effects, as well as a dummy variable indicating days following the receipt of a negative travel budget in the mobility report.

erage Indirect Effect (AIE). The latter captures the effect via the assumed mediator, whereas the former measures the sum of all other mechanisms. The absence of a statistically significant ADE in column (1) suggests that driving explains the entire effect on external costs or, alternatively, that all other effects add up to zero. Column (2) shows that the latter is the case: the external costs of transport are also affected by changes in public transport, bicycling, and walking, but these effects neutralize each other.

Table 5.11: Mediation analysis

	(1) Total ext. costs	(2) Total ext. costs	(3) Car cong. ext.
ADE	0.002	-0.009	-0.021*
	[-0.082,0.077]	[-0.083,0.061]	[-0.039,-0.001]
AIE (Car distance)	-0.215*	-0.218*	-0.047*
	[-0.371,-0.054]	[-0.376,-0.055]	[-0.081,-0.012]
AIE (Public transport distance)		0.033+	
		[-0.002,0.068]	
AIE (E-Bike distance)		-0.005**	
		[-0.009,-0.002]	
AIE (Walking distance)		-0.013**	
		[-0.023,-0.005]	
N	61’410	61’410	61’410

Notes: * p<0.05, ** p<0.01, *** p<0.001. The bounds show the 95%- percentile bootstrap confidence intervals (1’000 draws), which is the recommended choice for mediation analysis (Tibbe and Montoya, 2022). Columns (1) and (3) include car distance as the mediator variable. Column (2) incorporates all distances as separate mediators.

In column (3), we examine the mechanisms underlying the reduction in external congestion costs. Individuals essentially have two options to reduce these costs. They can (i) drive less or (ii) drive during less congested times. In theory, they could also drive in less congested areas, but we assume that the home and work locations are not changed due to a five-week treatment.

The significant and large AIE in column (3) indicates that the primary source of these reductions is indeed the decrease in car distances. However, the significant ADE suggests that individuals also shifted their car trips away from congested periods. In principle, both effects could take place at the same time if individuals replace car trips preferentially during congested times. However, even this interpretation is consistent with people not only adjusting the quantity of their driving but also the timing.

5.4 Discussion

In this section, we discuss threats to internal and external validity, both of which are of first-order importance to interpret our results. We conclude with the policy implications of our work.

Internal validity Empirical studies often face challenges with validity due to non-random treatment assignment or the lack of a pure control group. Our field experiment addresses both issues, enabling us to estimate causal treatment effects for our study sample. The assumptions required for the Difference-in-Differences approach have been demonstrated to hold wherever testable. In particular, we find no evidence for differential trends between the treatment and control groups during the pre-treatment period, which supports the assumption that any difference during the treatment period is caused by the treatment itself.

However, measurement error is a particular concern in this study due to the GPS-based data collection, which is imperfect, combined with the potential for individuals to modify the data. Appendix A.1.2 provides a detailed explanation of how alterations to the tracking data can be tested for. We find that treated individuals were not more likely to correct their imputed modes, but conditional on making a correction, they were more likely to correct their imputed modes away from car use, relative to the control group. This could be interpreted as evidence of cheating in the sense that (some) participants may have adjusted their reported modes strategically to reduce their external costs in the post-treatment phase. However, the absence of a measurable effect on corrections overall contradicts this interpretation, suggesting that participants did not make additional adjustments but simply paid more attention to car trips, as these were highlighted in the treatment e-mails. It remains therefore an open question whether the corrections were "honest", that is, whether an erroneously imputed car mode was accurately corrected to reflect the actual mode or strategically manipulated. Figure A.2 in the appendix shows that ignoring all participant corrections — whether truthful or otherwise — does not substantially weaken the results of the study. This also supports the reliability of the mode detection functionality in the tracking app. We conclude that whereas we cannot exclude the possibility that some participants manipulated the data in order to gain a financial advantage, these manipulations were not important enough to drive our results.

External validity The validity of field experiment results across contexts can be assessed through four points, as outlined by List (2020): selection into the study or into treatment groups, differential attrition and observability, the naturalness of the experimental setting, and the scalability of the findings. In the following, we discuss each of these in turn.

Selection Our experimental framework eliminates selection into treatment. However, potential bias may arise from the targeted recruitment process and participants' willingness to engage in the smartphone tracking study. Table 5.1 presents the socio-demographic characteristics of the final RCT sample in comparison to the relevant subpopulation from the Swiss Microcensus on transport (2023). Key differences include a lower proportion of individuals aged 18-30, and a higher proportion of males, urban residents, and fast E-bike owners in the RCT sample. Given that these characteristics modify the treatment effect (see section 5.3.3), it is to be expected that our results do not directly apply to all E-bikers in Switzerland, let alone to the entire population.

Knowledge of the conditional treatment effects allows us to compute the expected effect for a different sample, provided that there is common support among the key determinants. For example, we have computed the differential response of S-pedelec owners relative to owners of regular E-bikes, and it is therefore straightforward to compute the ATE for a sample in which the shares of these E-bikes are different. The same is true for all observable characteristics that we find to be modifiers of the effect.

Assessing a potential bias due to the self-selection into the smartphone tracking study is difficult. The participants are likely systematically different to those individuals who chose not to participate (at the very least, in their reluctance to be observed by a group of researchers). To the extent that the unobservable characteristics that co-determine participation are modifiers of the treatment effect, our results will be biased. Table 5.1 also aims at shedding some light into this concern by stating the sample characteristics of all individuals who were considered eligible during the introduction survey. Especially individuals aged 31-50 or 66-87 years, with secondary level education, or living with another person in their household were more reluctant to participate in the tracking study after completing the first survey.

We acknowledge this limitation of our study and cannot determine the magnitude or direction of this self-selection bias. Our results are based on the responses of people that were willing to fill out a survey on E-biking and agreed to being GPS-tracked. Nevertheless, if some form of transport pricing were to be implemented in a voluntary manner in exchange for some other tax relief, our sample would constitute a good basis to predict the treatment effect of such a program.

Attrition and observability Attrition is hardly avoidable in a field experiment, and it poses a concern when participants who complete the study differ from those who do not. If completion probability is related to key outcome variables, such as car distance, treatment effects may be biased. Another concern is that attrition varies by treatment status. Both potential sources of bias can be assessed through a regression analyzing the determinants of attrition. Appendix A.1.3 demonstrates that neither treatment status nor outcome variables significantly influence the observability of individuals in the treatment phase.

Naturalness A key consideration when interpreting experimental results is the naturalness of the task under consideration. In this study, we observed people in their regular environment as they make everyday transport choices. This is a key advantage of a natural field experiment such as ours, relative to more artificial settings such as laboratory experiments or field experiments in which the participants have to perform a task that they usually would not carry out.

The most "unnatural" part of the experiment is the implementation of the Pigovian tax as a deduction from a travel budget that we previously assigned to the participants. Although equivalent in strictly microeconomic terms, it is unclear whether the (psychological) effect of reducing this budget is equivalent to that of imposing an actual tax. Without governmental authority, the approach chosen in this study is the most suitable approximation of an actual tax, in our opinion. Since participants were not obliged to pay for external costs that exceeded their budget, our study can only estimate a substitution effect, as the income effect of the tax is compensated for by the individualized budget. Furthermore, there may be a behavioral distinction between receiving less money and paying taxes directly from one's own assets. Thaler and Johnson (1990) suggest that people often treat gambling money differently from their regular income, blending prior gains with subsequent losses and viewing losses smaller than the initial gain as less significant. This can encourage risk-seeking behavior, potentially leading to an underestimation of the effect that would result from transport pricing which is deducted from households' actual income.

Scaling An important aspect is the extent to which the experimental results are likely to scale to different populations. Scaling can take three qualitatively different forms. First, horizontal scaling determines how the treatment effects generalize to different samples in the sense that the same experiment would be carried out elsewhere. Regional variations, such as the high quality of the Swiss public transport network, may limit horizontal scalability in our context, and thus also external validity. On the other hand, our main effect consists of a reduction in driving combined with an increase in E-biking, which is not directly related to the quality of public transport. The quality of cycling infrastructure and overall cycling safety is another matter. We do not expect our results to translate to settings in which bicycling is perceived as much less safe than in Switzerland.

Although the study covers a broad sample of adults aged 18 and older, it focuses on E-bike users who still regularly drive. Charging for marginal external costs may lead to smaller (absolute) treatment effects for individuals who are non-E-bikers or do not drive regularly, as the latter typically generate lower levels of daily externalities. Seasonal variation is another potential dimension. Our treatment effect is a weighted average of the effects observed in autumn and spring. Although no significant differences were found, the varying point estimates suggest potential seasonal variation, which could be further explored in future research.

Second, vertical scaling considers the impact of extending the treatment to a larger share of the population. Implementing a nationwide Pigovian tax on transport externalities would involve higher administrative costs but also general equilibrium effects that could shape its effectiveness. The policy's effectiveness in reducing car kilometers traveled and encouraging shifts to more sustainable modes would naturally lead to less congested roads and potentially more cyclists. However, this reduction in congestion could, in turn, attract additional car trips due to shorter travel times and discourage some individuals from cycling due to increased bicycle lane traffic. These feedback loops could shift the equilibrium, affecting external costs and thus the marginal rates of external costs that determine the tax itself. Such dynamic adjustments are challenging to capture within the scope of this field experiment. However, they could be observed through quasi-random empirical studies in real-world implementations.

Finally, the results should also be scalable with respect to time. The five-week tax exposure in this study likely captures short-term behavioral changes, focusing on intensive-margin effects, but may not account for long-term decisions such as changes in mode tool ownership or residential location. Consequently, our estimates might understate the effects of prolonged exposure to a Pigovian tax on transport externalities. In absence of direct evidence, long-term effects may be approximated from studies on fuel price elasticity, where findings by Goodwin et al. (2004) indicate that "long-run elasticities are greater than short-run elasticities, mostly by factors of 2–3".

Policy implications This study shows the effectiveness of reducing the external costs of transport through the implementation of a first-best Pigovian tax. To assess the policy's social desirability, a welfare analysis is required, considering the benefits of reduced external costs, the welfare loss due to individuals' re-optimized mode choices, and the administrative costs of policy implementation. For a detailed estimation of the welfare consequences, including changes in consumer surplus, we refer to the forthcoming published version of this paper, where these effects will be analyzed using a discrete choice model.

In a closely related study, Hintermann et al. (2025) conducted a similar analysis, estimating a monetized utility loss of 2.90 CHF per day as the deadweight loss from taxing external costs. After subtracting the redistributed lump-sum revenue, the net welfare gain from the reduction in external costs amounts to 140 CHF per person annually. Based on these findings, they conclude that implementing such a Pigovian tax is socially desirable, as the welfare benefits outweigh the costs.

Building on the work of Hintermann et al. (2025), where the limited number of cyclists constrained a detailed analysis of cycling behavior, we observe a substantial shift in travel distances from cars to E-bikes. Notably, faster E-bike models are more likely to replace cars than slower ones. Importantly, while the total travel distance remains unchanged, we find that people not only reduce car travel distances but also shift away from congested time windows.

As E-bikes likely continue to grow in popularity, our findings highlight their potential to play a significant role in shaping future transport choices. Additionally, the insights gained from this study are applicable to other policies that affect transport prices. Given the generalizability of our results, they are informative for policies that alter the relative costs between transport modes in similar magnitudes.

6 Carbon emission reductions attributable to E-Biking

E-bikes present a sustainable alternative to motorized transport, promising reductions in CO_2 emissions (see, e.g., Bucher et al., 2019; McQueen et al., 2020; Moser et al., 2018; Philips et al., 2020, 2022; Sacchi and Bauer, 2023a). In this chapter, we compute the impact of E-bikes on CO_2 emissions in the transport sector in Switzerland. We do this both for the status quo - in other words, a what-if scenario which compares current E-bike use to a situation without any E-bikes - as well as for different future scenarios.

The primary challenge consists of identifying which travel modes have been, and will be, replaced by E-bikes. Substitution of car trips will result in carbon savings; on the other hand, substitution of cycling and/or walking will result in (small) increases in emissions. The substitution pattern is therefore a key component in the computation of the current and future carbon savings from E-biking.

However, the substitution behavior associated with E-biking is not directly observable. Conceptually, measuring substitution entails accurately assessing travel behavior prior to (any) use of E-bike, observing some form of intervention that introduces the E-bike as an available transport option (e.g., the purchase of an E-bike or obtaining access to shared or rented E-bike), and finally accurately observing travel behavior again, now including the E-bike as one of several competing modes. In practice, a prospective assessment of E-bike adoption along the sequence outlined above is not feasible, mainly because assessing travel behavior and following a study population large enough to yield a substantial sample of E-bike purchases over time would be very costly.

As a compromise, the previous literature has applied three main alternative research designs: In limited trials, a specific study population is identified (typically employees of a company, or similar), provided with access to E-bikes and followed prospectively. This allows for "real time" observation of substitution behavior, however, trial participants may not be representative of the general population, and the costly intervention will limit the sample size, and therefore statistical power (i.e. ability to draw conclusions)(see, e.g., Sundfør et al., 2024; Moser et al., 2018; Andersson et al., 2021).

Substitution behavior can also be assessed retrospectively - in other words, in subjects who have already adopted E-bike use - typically using surveys. Accurate recall of travel behavior with and without an E-bike poses the main challenge of this approach. The majority of published studies on the topic used such a retrospective ("What did you use for this trip in the past?") or hypothetical ("What would you use if E-bike was not available?") approach. See Bigazzi and Wong (2020) for an overview.

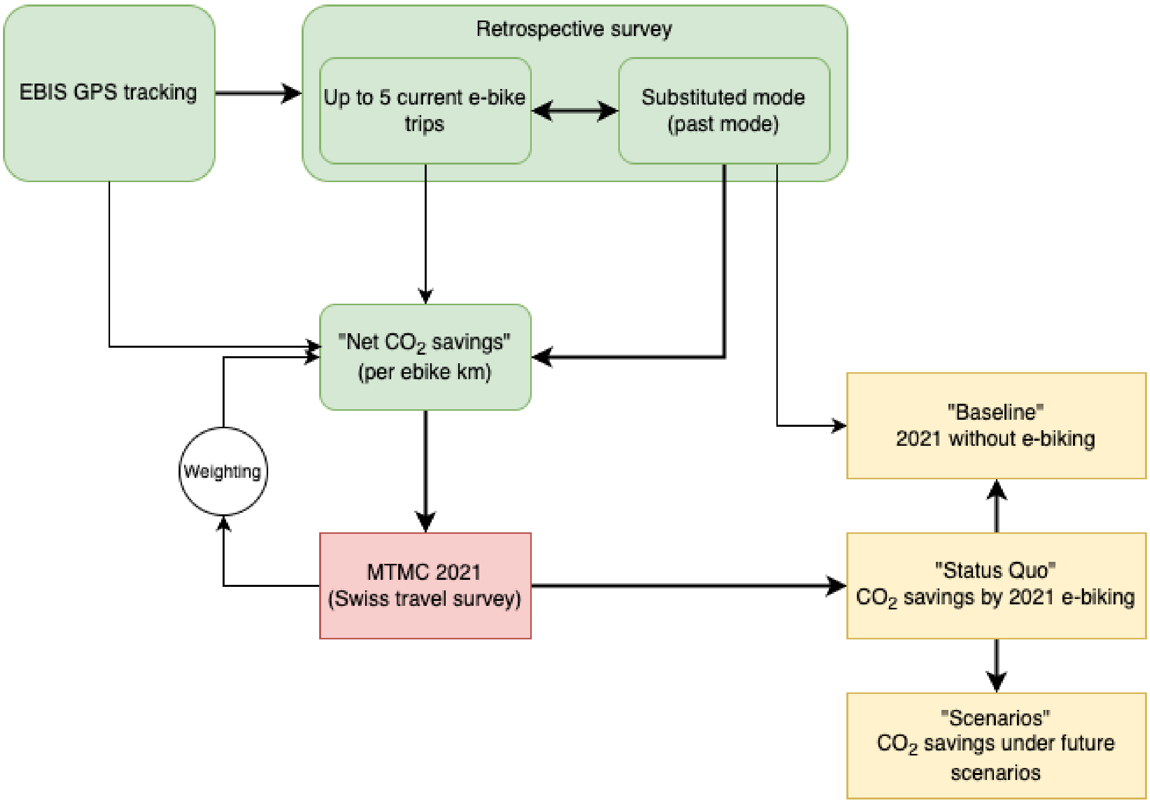
EBIS applied a retrospective survey. Compared to previous studies, the tracking of current E-bike trips promises to minimize recall bias (error in reporting because of the difficulty to remember past trips). Presenting participants with detailed information about E-bike trips which they actually and fairly recently took, made the question about their hypothetical "past" mode choice, had they not used an E-bike, more tangible than if the question was phrased in more general terms (see section 3.1.4).

A third alternative to explore substitution behavior is to estimate mode choice models. Mode choice models estimate "utility" of a trip based on trip attributes (i.e. distance, cost, etc.), and then predict mode choice based on which mode would yield the highest utility. Given a successful model estimation, the resulting coefficients allow to predict the most likely substituted mode. In practice, the implementation of this approach is challenging. It requires the observation of relevant mode choices and relevant trip attributes, requiring substantial data collection efforts, including, but not limited to, GPS tracking. The approach is as reliable, as we have confidence in the prediction coefficients: if easily measurable attributes, such as duration or cost, drive the choice, the predictions will be more robust than if perceived safety, or aesthetics of routes determine mode choice. For an example of this approach, see Reck et al. (2022) [21] Since in EBIS the tracking app was unable to differentiate between regular bicycles and E-bikes, we cannot observe the choice between bicycle and E-bike, and hence cannot derive substitution rates applying this approach.

6.1 Data

We combine several data sets and compute several outcome measures of interest. An overview of the workflow is provided in Figure 6.1.

Figure 6.1: Workflow combining EBIS tracking and survey data with MTMC data to estimate nation-wide carbon emission savings



[21] Reck et al. (2022) derive mode substitution among current E-bike-users estimating a mode choice model based on GPS-tracked trips, rather than a retrospective survey.

To estimate carbon emission savings from E-biking we combine data from several sources: 1) trip data from tracking, 2) survey data including subject attributes and the "retrospective survey" module inquiring about substituted modes, 3) carbon emission factor data for the various travel modes, and 4) the Swiss Mobility and Transport Microcensus (MTMC) to scale the emission calculations to the entire Swiss population. In the following, we describe these datasets.

6.1.1 Tracking data

The tracking data is the principal data collected in this project and is described in more detail in Section 3. For the calculation of CO_2 savings by E-biking, we focus on E-bike trips only (groups A and B). Aside from the chosen mode, the tracking data includes accurate (objective) information on trip distance and duration. To this, we merge weather data and the participant-specific data from the survey, such as socio-demographic characteristics.

6.1.2 Retrospective survey

Based on tracking during the first phase, up to five recent trips were presented to participants in the retrospective survey (see Section 3.1.4). The trips presented in the retrospective survey were automatically selected among the tracked trips by an algorithm integrated into the tracking data collection pipeline. To be included, a trip had to be at least 2 km long (shorter trips would not affect overall CO_2 emissions much, and as such not justify imposing such survey burden on participants), and distinct from previously presented trips (defined as origin or destination to be at least 500 meters apart). These trips were presented in the form of a map indicating the route, date and time, and the mode used.

The participants were first asked to confirm that this trip had indeed ben taken by E-bike, and then to indicate which mode they would have used for this same trip, if any, prior to using an E-bike. The offered alternatives were car, public transport, conventional bicycle, and walking. We refer to the answer provided by the respondents as the “substituted” mode. This reflects our “ground truth” of substitution behavior for the participants in EBIS, and more specifically, for the E-bike trips we asked them about in the retrospective survey. All substitution estimates in this section, including for other trips by the same people and trips by different people, are ultimately based on these answers.

The survey also captured vehicle ownership information (incl. car size and fuel type) and socio-demographic data used to match CO_2 emission factors and to weigh the data (see below). After combining tracking and survey data, overly long trips (>2 h) and those with unrealistic speeds (35 km/h for regular E-bikes, 50 km/h for S-pedelecs, 150 km/h for car and public transport) were excluded, reducing the sample by approx. 250 records.

6.1.3 CO_2 emission factors

For the calculation of net CO_2 emission reduction factors (ERF's) for E-bike trips in the EBIS data, Mobitool[22] emission factors were used. These are based on a life-cycle assessment of the respective modes of transport in terms of emission (Sacchi and Bauer, 2023a). The factors account for the average emission per km across the fleet of Switzerland and take into account vehicle size and fuel type. When calculating CO_2 emissions in the MTMC data, for car trips only, the emission factors provided in the MTMC data were used.

6.1.4 Mobility and Transport Microcensus (MTMC)

The MTMC 2021 is a representative household travel survey of approx. 50k subjects (age 6 and up) based on a 1-day travel diary. Using travel data from this representative population survey served two purposes: To weigh the EBIS data to make it representative of the Swiss E-biking population in terms of socio-demographic variables, and to scale the results to reflect nationwide CO_2 savings in Switzerland.

6.2 Calculation of substitution rates and CO_2 emissions

6.2.1 Weighting the EBIS sample to be representative of Swiss E-bikers

When assessing substitution behavior in the EBIS sample, we weigh the data to take on equal distributions in key variables that are present in the MTMC sample. Most importantly, the EBIS retrospective survey sample consists exclusively of E-bike trips (of which 44% are carried out by regular E-bikes and 56% by S-pedelecs), whereas the MTMC data only includes 1% regular E-bike and 0.2% S-pedelec trips. The EBIS sample is furthermore skewed towards more male and younger participants, while the E-bike trips are slightly longer on average than in the MTMC. To make the different samples comparable, we therefor weigh by E-bike type, gender, age group ("<18", "19-35", "36-50", "51-65", "65+"), and trip distance category (0-10km 10-20km, 20+km).

6.2.2 Deriving mean net CO_2 emission reduction factors

Emission factors were applied to both the E-bike trip as well as the substituted mode in the retrospective survey. For this, we make use of the detailed information from the survey that includes information about respondent's car (size and fuel type). Where vehicle size and fuel type was not available (for example, if someone indicated the car as the substituted mode but longer owns one), we use fleet averages instead.

We then calculate emission reduction factors (ERF's) in the sense of the net CO_2 reduction per km E-biking by subtracting the emissions associated with the observed E-bike trip[23] from

[22] https://www.mobitool.ch/de/tools/mobitool-faktoren-v3-0-25.html

[23] E-bikes cause 10-11 grams of CO_2 per km due to electricity production and the bicycle itself (Life cycle emission factors). Source: Mobitool

the emissions of the substituted mode, divided by the distance. The ERF is positive if the substituted mode is car or public transport, but negative if the E-bike substituted a regular bicycle or a walking trip.

Since not every E-bike km will result in the same amount of CO_2 reduction due to differences in the substituted mode, we control for potentially influential variables by applying the weights discussed above.

We compute ERFs for three different levels of aggregation: (i) all E-bike trips; (ii) separately by type of E-bike (regular or S-pedelec); and (iii) separately by stratum defined by E-bike type, age group, gender and distance category.[24] It is this finest level of aggregation that we use to compute the estimated CO_2 savings due to E-biking, whereas the higher levels of aggregation are shown mainly for illustrative purposes in the sense of how much CO_2 is saved by a typical E-bike trip.

6.2.3 Estimating net CO_2 savings by current E-biking in MTMC data

We apply the net CO_2 ERF's to current E-biking trips in the MTMC. We focus on strata-based ERF's and consider the cruder estimates in sensitivity analysis (see appendix A.2). The ERF's are based on the emission factors shown in Table A.8. We measure net CO_2 savings in different ways:

- the average net CO_2 savings per E-bike trip
- the total sum of CO_2 savings from all E-bike trips in Switzerland
- the reference value for these prior to any E-bike use
- the relative change in CO_2 emissions due to E-biking

For these calculations, the ERF's are multiplied with the trip distance to arrive at a total amount of emissions reduction. To aggregate estimations for all of Switzerland based on MTMC data, we apply the provided person weights and a population-extrapolation factor to scale from the survey sample to the entire Swiss population (i.e., 8.7 million in 2021). The emissions are converted into tons of CO_2 per year.

When calculating nationwide impacts of E-biking on CO_2 emissions, we present the results as both *absolute* reductions (in tons nationwide), as well as *relative* reductions (in %). For the latter, the reference sample representing the total (i.e. 100%) is key and will depend on the context. More specifically, we provide relative reductions attributable to E-biking based on the following reference samples:

- **E-bike trips only** (by how many % does E-biking reduce CO_2, compared to modes previously used for these trips?)
- **All trips taken by E-bikers** (by how many % do E-bikers reduce their transport related carbon footprint[25], compared to before using an E-bike?)

[24] More refined (disaggregated) ERF's allow to better reflect differences between E-bike trip types, but run the risk to produce less accurate estimates for strata with few observations.

[25] Not including air travel and trips abroad

- **Trips shorter than 10 km** (by how many % are emissions reduced among trips up to 10 km? (presumably the main "market" for biking)
- **all trips** (by how many % does E-biking reduce CO_2 emissions, relative to total ground transportation in Switzerland?)
- **trips within large agglomerations** (By how many % are emissions reduced among trips within major agglomerations[26]? (presumably a main "market" for biking)

These different reference samples basically provide different options to present and communicate the results, but do not actually affect the absolute emission estimates.

6.2.4 Estimating net CO_2 savings from hypothetical future scenarios

Last, we estimate net CO_2 savings based on different scenarios, which shift trips from various modes to E-biking. For each scenario formulation, a target number of trips to be shifted is calculated. These trips are then randomly drawn from among the target trips, which are all trips that currently are not carried out by E-bike.

To reflect the fact that not all trips are equally likely to be replaced by an E-bike, we compute "propensities to shift to E-bike". For this, we consider trip length, age and gender distribution of current E-bike trips in the MTMC, as well as the mode substitution rates from the EBIS retrospective survey. In other words, we take account of the fact that a bicycle trip of 5 km is more likely to be replaced by an E-bike than a car trip of more than 30 km. This procedure ensures that the artificially shifted trips are similar to current trips in terms of the modes that they substitute, and in terms of trip distance.

The selection of scenarios aims to illustrate various ways of how goals to increase E-biking may be formulated. Specifically, the following scenarios were assessed:

Pre-E-bike: This scenario represents a hypothetical "past" baseline based on 2021 travel, in which E-bike trips have been replaced with substituted modes. It serves as a reference point "prior to any E-biking" to illustrate the effects of current E-biking.

Status quo: Current (2021) levels of E-biking. This corresponds to the calculations outlined in the previous subsection.

Increase E-bike 2-, 5-, or 10-fold: These scenarios multiply the number of E-bike trips relative to the current E-bike share, which is 1.2% of all trips.

Everyone like current E-bikers: This scenario calculates the current share of E-bike trips among E-bike owners and applies this share to the entire population. In other words, it assumes that the E-bike usage pattern of current E-bike owners is adopted by everyone.

[26] Approx. 50% of all trips take place within agglomerations

Shift 10% or 50% of non-E-bike trips to E-bike: These scenarios increases the number of E-bike trips by shifting a percentage of non-E-bike trips to E-bike.

Shift 50% of non-E-bike trips to E-bike assuming 50% E-cars: Same as above but assuming that 50% of car trips are carried out by electric vehicles. This reduces the emission reductions, as EV's have lower emissions than conventional cars (which constitute the vast majority in the MTMC sample).

Shift 50% of non-E-bike trips of 5-10km length to E-bike: This scenario targets trips in a length segment considered well within reach of E-biking.

All E-bike: In this scenario, all trips are switched to E-bike trips. This represents a hypothetical situation where E-bikes completely replace other modes of transportation. For this scenario, neither propensities nor weights are necessary.

6.3 Results

6.3.1 Descriptive statistics

In total, 6,111 E-bike trips were presented to 1,596 current E-bikers as part of the retrospective survey. Approx. 40% of participants were presented five distinct trips, and 75% responded to at least three trips. Table 6.1 presents descriptive statistics for the E-bike trips included in the retrospective survey.

Table 6.1: Descriptive Statistics by E-bike Category (EBIS)

Variable	Category	E-bike (25 km/h) (n = 2439)	S-pedelec (45 km/h) (n = 3130)
Age		51.2 (51.2)	49.3 (49.3)
Length (km)		5.6 (4.4)	7.7 (6.2)
Average Speed (km/h)		17.7 (17.7)	23.5 (23.5)
Gender	Female	1245 (51%)	1000 (31.9%)
	Male	1194 (49%)	2130 (68.1%)
Age Group	0-18	0 (0%)	11 (0.4%)
	19-35	246 (10.1%)	306 (9.8%)
	36-50	960 (39.4%)	1303 (41.6%)
	51-65	844 (34.6%)	1329 (42.5%)
	65+	389 (15.9%)	181 (5.8%)
Length Interval	0-10km	2160 (88.6%)	2362 (75.5%)
	10-20km	234 (9.6%)	586 (18.7%)
	20+km	45 (1.8%)	182 (5.8%)

Table 6.2 compares the characteristics of the E-bikes among the EBIS participants with the E-bikers in the MTMC.

Most obviously, the split between regular E-bikes and fast S-pedelecs in EBIS tilts heavily towards S-pedelecs (56%), at least partially by design, as we were able to contact/recruit fast

Table 6.2: Comparison of E-Biking in EBIS and MTMC

		Regular E-bike (25 km/h)			S-pedelec (45 km/h)		
Variable	Category	EBIS	MTMC	p	EBIS	MTMC	p
E-bike Type		43.8	81.9	***	56.2	18.1	***
Gender	Male	49.0	43.3	***	68.1	58.3	***
	Female	51.0	56.7	***	31.9	41.7	***
Age Group	19-35	10.1	11.6	***	9.8	15.5	***
	36-50	39.4	27.9	***	41.6	35.9	***
	51-65	34.6	32.9	***	42.5	37.7	***
	65+	15.9	21.0	***	5.8	8.4	***
Trip Length Interval	0-10km	88.6	89.6	**	75.5	81.4	*
	10-20km	9.6	6.8	**	18.7	14.2	*
Trip Duration Interval	0-15min	50.1	56.2	***	49.8	48.6	*
	15-30min	35.5	25.2	***	33.8	32.6	*
	30-45min	7.9	6.8	***	10.3	9.3	*
	45-60min	4.0	1.8	***	4.0	5.3	*
	60+min	2.5	10.0	***	2.1	4.2	*

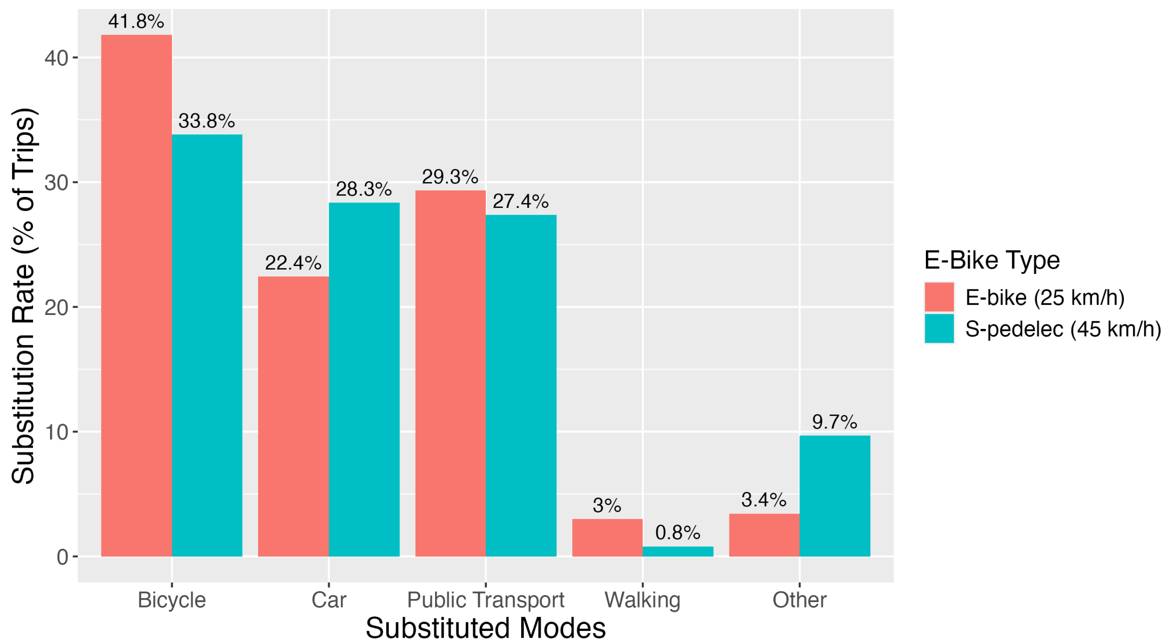
Note: *** = p value < 0.001, ** = p value < 0.01, and * = p value < 0.05.

E-bikers through the vehicle registration agency in Zurich and Basel. Registration is mandatory for fast S-pedelecs, but not for regular E-bikes. Within the two E-bike type groups, the characteristics of the two samples track more closely, though most differences are statistically significant.

E-bikes substitute for conventional cycling, driving (car), and public transport trips in roughly equal parts in our sample (Figure 6.2).

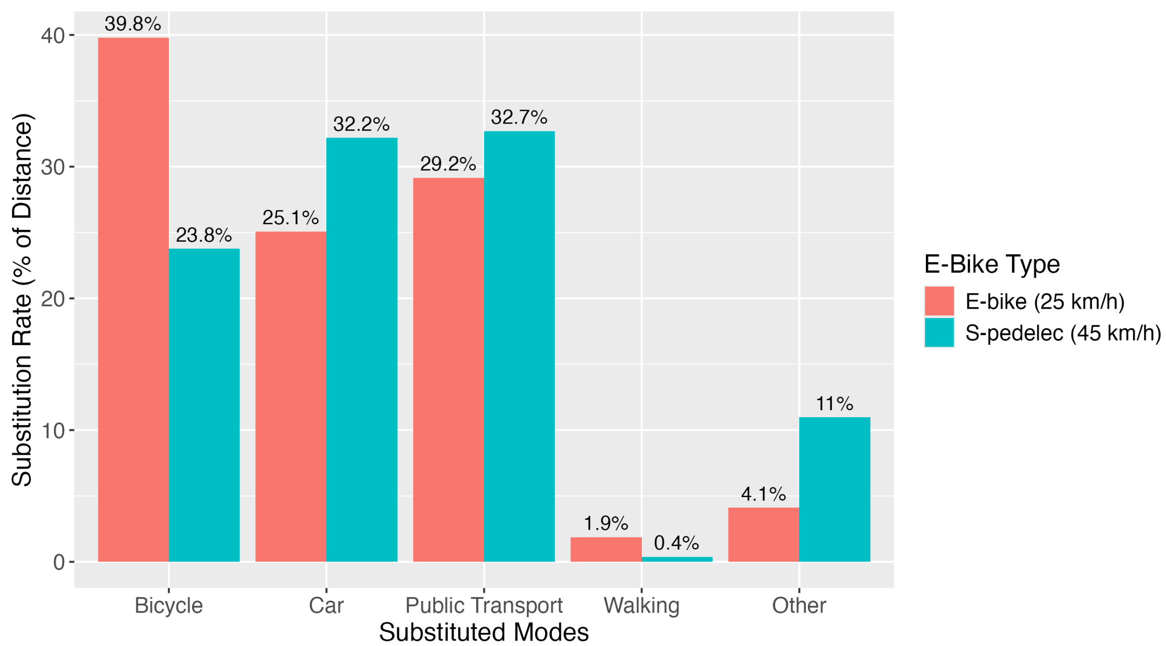
In terms of distance - the more relevant measure in the context of emission assessments - regular E-bikes substitute to a greater extent for conventional cycling (40%), while 60% of S-pedelecs substitute for driving and public transport (Figure 6.3). Substitution of one E-bike type for the other was negligible; only 3% of fast S-pedelec trips came from regular E-bikes, and none switched from fast to regular E-bikes. Over 90% of E-bike trips were taken to the same destination as the trip prior to ebike use.

Figure 6.2: Mode substitution rates for E-bikes based on trips



Note: This figure shows the percentage of trips that were substituted by the E-bike, separately for the regular and fast versions. Reading example: Among regular E-bike users, 41.8% of the trips in the retrospective survey were previously taken by regular bicycle.

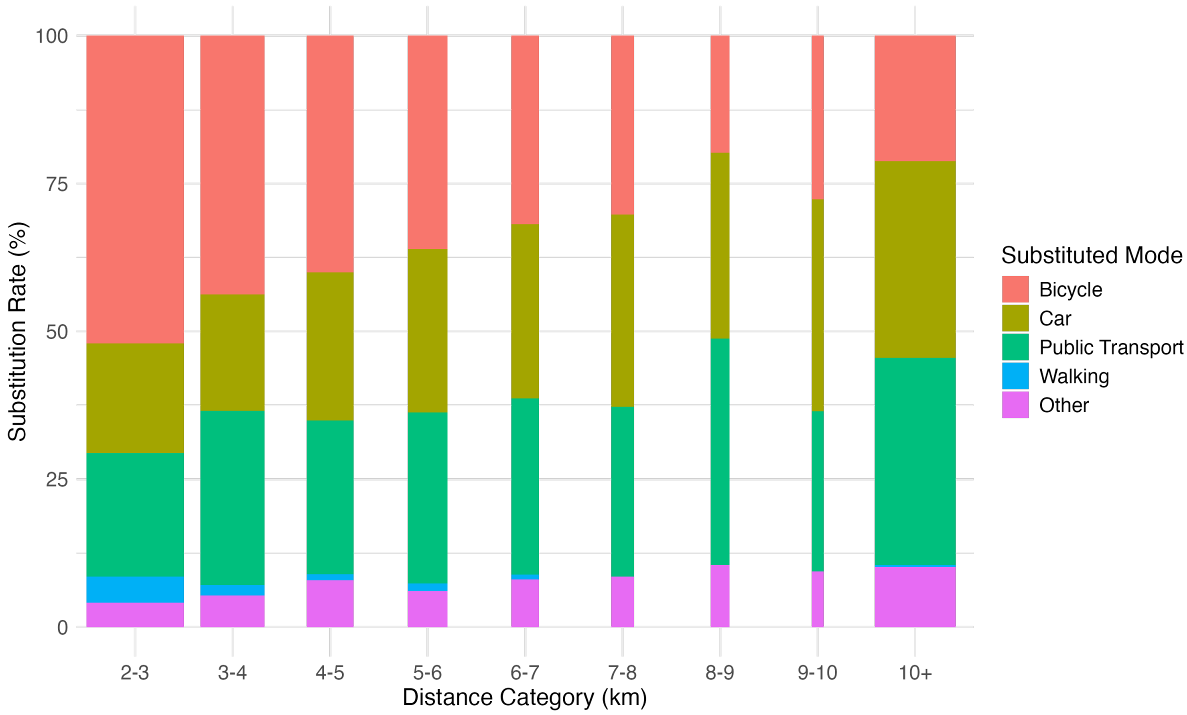
Figure 6.3: Mode substitution rates for E-bikes based on distance



Note: This figure shows the percentage of distances that were substituted by the E-bike, separately for the regular and fast versions. Reading example: Among regular E-bike users, 39.8% of the distances in the retrospective survey were previously carried out by regular bicycle.

Whereas more than half of all short trips (<3km) substitute for conventional cycling, substitution of motorized modes increases with trip distance (Figure 6.4). More detailed substitution rates are presented in Table A.9 in the appendix.

Figure 6.4: Mode substitution rates by trip distance



Note: This figure shows the percentage of trips that were substituted by the E-bike, separately for different distance categories. Reading example: Among E-bike trips with a distance from 2-3 km, over 50% replaced regular bicycles, around 20 % were replaced a car, and 25% replaced public transport. The retrospective survey was restricted to trips of at least 2 km. The width of the bars represents the quantity of trips in each distance bin.

6.3.2 CO_2 emission reductions due to E-biking

E-bike trips in the EBIS retrospective sample reduce CO_2 emissions by 42 grams per km, on average. This value is considerably less than typical emissions per km by car (approx. 186g), because there is relatively little CO_2 reduction from E-bike trips substituting for public transport, and (small) CO_2 increases from E-bike trips substituting for conventional cycling and walking.

When assessing emission reductions in the MTMC data in the sense of using ERF's to calculate country-wide emissions, we cannot rely on substituted modes as these are unobserved. Hence, we apply the ERF's derived in the EBIS sample. To do so, we need to understand if it is adequate to apply a single mean ERF value for all E-bike trips, or whether trip and/or rider attributes (i.e. E-bike type, age, gender, trip distance) affect ERF values and should therefore be taken into account.

Calculating ERF's for various subgroups, shows that ERF's are somewhat higher for men than vs. women (-44.6 g vs. -38.0 g), faster S-pedelecs than regular E-bikes (-46.0 g vs. -

Table 6.3: Net CO_2 Savings per km in EBIS, by Strata.

Mode	Age	Sex	Length Interval	CO2 per km	Trips (N)
E-bike (25 km/h)	19-35	F	0-10km	-24.8	147
			10-20km	-81.2*	11
		M	0-10km	-20.3	86
			10-20km	5.7*	2
	36-50	F	0-10km	-35.9	507
			10-20km	-28.7*	20
			20+km	-29.8*	10
		M	0-10km	-37.1	369
			10-20km	-53.9	46
			20+km	-59.8*	8
	51-65	F	0-10km	-39.5	405
			10-20km	-35.3	53
			20+km	-124.2*	4
		M	0-10km	-39.9	323
			10-20km	-62.2	49
			20+km	-46.3*	10
	65+	F	0-10km	-40	78
			10-20km	-46.3*	7
			20+km	-61.2*	3
		M	0-10km	-32.5	245
			10-20km	-19.8	46
			20+km	-13.1*	10
S-Pedelec (45 km/h)	0-18	F	0-10km	-36.5*	9
		M	0-10km	4.2*	2
	19-35	F	0-10km	-39.6	108
			10-20km	-25.3*	22
			20+km	-40.2*	4
		M	0-10km	-35	132
			10-20km	-61.4	40
	36-50	F	0-10km	-37.6	377
			10-20km	-79.1	61
			20+km	-27.2*	9
		M	0-10km	-45	619
			10-20km	-57.6	171
			20+km	-47.6	66
	51-65	F	0-10km	-37.8	335
			10-20km	-41.2	53
		M	0-10km	-47.8	630
			10-20km	-55.9	211
			20+km	-65.4	100
	65+	F	0-10km	1.1*	20
			10-20km	-78.1*	2
		M	0-10km	-42	130
			10-20km	-75.4*	26
			20+km	-64.1*	3

Note: * estimates based on less than 30 trips.

36.6 g), middle age groups, and longer trips (approx. 55 g vs 39 g for trips <10 km). When combining all variables to create refined strata based on E-bike type, age, gender, trip distance, the resulting ERF's range from +6g to -124g. However, almost half of these strata are based on less than 30 trips. When focusing on the more robust estimates, the ERF's range from -20g to -80g per km. These values are displayed in Table 6.3. The results in terms of carbon savings presented in this chapter are based on these strata-based ERF's. Using the overall mean ERF, the emission reduction would be 35% higher.

Table 6.4 presents the CO_2 emissions reductions associated with the status quo. These are the carbon savings attributable to current (2021) levels of E-biking, relative to a hypothetical baseline of current travel without any E-biking. The table shows that current E-biking avoids 22'000 tons of CO_2 per year, or around 78% of emissions previously caused by these trips. E-bikers reduce their transport-related carbon foot prints by about 18% (domestic ground transport only). This is equivalent to 0.62% of emissions from all short trips (up to 10 km), and 0.17% of total transport emissions.

Table 6.4: CO_2 reductions attributable to Status Quo (2021), nationwide total (tons)

	Scenario	Total CO2 Reduction Nationwide	Total Reference CO2 Nationwide	Percent Change Total Nationwide
E-bike trips only	Status quo (2021)	-22,441	28,644	-78.34
All trips by E-bikers	Status quo (2021)	-22,441	125,146	-17.93
Trips 10km	Status quo (2021)	-14,341	2,297,979	-0.62
Large Agglo's	Status quo (2021)	-13,974	7,712,499	-0.18
All trips	Status quo (2021)	-22,441	13,141,787	-0.17

Note: ERF type: strata.

Table 6.5 shows CO_2 reduction effects for the various scenarios. Here we use "All trips" as the reference dataset. We also computed results for the alternative reference datasets "Trips <10km" (approx. 20% of all distances) and "large agglomerations" (approx. 50% of all distances); the results can be found in appendix A.2.[27] All scenarios increase E-biking through shifting non-E-bike trips to E-biking but without assuming a particular mechanism to effectuate such a shift; for an analysis of the increase in E-biking among E-bikers in response to Pigovian pricing, see Section 5.

To provide a reading example, the table shows that doubling E-biking (in terms of the number of trips) will more than double the emissions reductions (to 51,793 tons of avoided CO_2). The relationship is not linear because the new E-bike trips tend to be a bit longer and/or

[27]The different reference datasets provide some help in assessing the significance of the CO_2 reductions. Namely, short trips (<10km) or urban trips (large agglomerations) may reflect the type of travel most likely to shift to E-biking, while using all trips allows to assess the relative contribution (i.e. reduction) to all transport emissions.

Table 6.5: CO_2 reductions attributable to Scenarios, nationwide (tons); (Reference dataset: All_trips)

Scenario	Total CO2 Reduction Nationwide	Total Reference CO2 Nationwide	Percent Change Total Nationwide
Baseline	0	13,141,787	0.00
Status quo (2021)	-22,441	13,141,787	-0.17
Increase E-bike share 2-fold	-51,793	13,141,787	-0.39
Increase E-bike share 5-fold	-126,751	13,141,787	-0.96
Increase E-bike share 10-fold	-242,775	13,141,787	-1.85
Everyone like current E-bikers	-1,220,306	13,141,787	-9.29
Shift 10% of non-E-bike trips to E-bike	-171,200	13,141,787	-1.30
Shift 50% of non-E-bike trips to E-bike	-641,387	13,141,787	-4.88
Shift 50% of non-E-bike trips to E-bike, 50% cars electric	-501,938	10,389,005	-4.83
Shift 50% of non-E-bike trips of 5-10 km to E-bike	-636,283	13,141,787	-4.84
All trips by E-bike	-11,834,706	13,141,787	-90.05

Note: Reference dataset: All_trips. ERF type: strata.

associated with higher emissions than the trips that have already been replaced. Shifting 10% of current non-E-bike trips to E-bike will increase total CO_2 reduction due to E-biking from 22'441 tons to 171'200 tons. Similarly, shifting 50% of non-E-bike trips of length 5-10 km would yield 636'000 tons of avoided CO_2. This figure is basically the same as shifting 50% of all trips, because the vast majority of E-bike trips are less than 10 km, and our algorithm assures that shifted trips mimic the length distribution of current trips. Using the 50% shift scenario, we can also assess the influence of an increasingly electrified car fleet. High shares of e-cars will reduce the impacts of E-biking by approx. 20% lower net emission savings.

6.4 Discussion

E-biking in Switzerland substitutes for conventional cycling, public transport, and driving to approximately equal parts, and as such confirms findings in the international literature (Bigazzi and Wong, 2020; Chevance et al., 2025). Given the high levels of public transport use and relatively high conventional cycling rates (5%) in Switzerland, substitution of these zero or low polluting modes is considerable. While this may appear as undesirable from a carbon emissions perspective, there are other benefits attached to replacing public transport trips in terms of the health benefits from cycling, and also in terms of system capacity concerns.

E-biking, despite its rapid growth over the past years (See Figure 1.1), is still a rare mode of travel in Switzerland, with 1% of all trips take by regular E-bikes, and 0.2% by fast S-pedelecs. Consequently, the emission reductions by current levels of E-biking are relatively small, compared to total emissions of land transport, at 0.17% (22'441 tons). Nevertheless, the average E-bike trip reduces emissions by 78%, compared to the prior mode used for that same trip, and current E-bikers reduce their personal transport-related carbon footprint by 18%. This finding is comparable to a US study, which estimated personal CO_2 potential at 12% (McQueen et al., 2020).

If valued at a Social Cost of Carbon of 430 CHF/ton proposed by the Swiss Federal Office of Spatial Development, these reductions add up to CHF 9,6 million annually. To put this in perspective: In 2015, Zurich voters approved a CHF 120 million investment over 20 years for cycling infrastructure, including bike lanes and parking facilities.[28] Bern's Velo-Offensive aims to increase the cycling share of total traffic from 11% (as of 2010) to 20% by 2030.[29] The city has allocated CHF 2.45 million annually for promoting pedestrian and bicycle traffic, up from a previous budget of CHF 1.25 million.

For a more adequate comparison, however, other potential benefits (and costs) should be factored in to decision-making. The Swiss government estimates external net benefits from E-biking of CHF 180 million per year, of which the vast majority is due to health benefits from physical activity and costs due to injuries (Ecoplan and INFRAS, 2024). Climate effects were not assessed, due to the unknown substitution pattern. In particular for regular E-bikes the benefits dominate, whereas for S-pedelecs the additional injury costs offset 90% of the benefits. On the other hand, our findings point to significantly greater emission reductions by the faster S pedelecs, as these are better suited to substitute for longer trips and/or car trips. However, efforts to specifically promote these for work commutes etc. should be paired with prudent monitoring of traffic safety concerns, as the higher speeds clearly raise potential crash and injury risk. Empirical data to substantiate such concerns, however, are still scarce, as the prevalence of S-pedelecs is still very low.

Further, E-bikes, just like regular bicycles, are relatively space efficient vehicles (and even more so, at high mode shares, as seen e.g. in the Netherlands). Such, and related benefits in the transport and urban planning domain are typically not quantified in cost-benefit assessments of (E-)biking, or transport more generally.

A growing body of literature supports our general patterns on mode substitution rates, though generalizability of such studies is typically limited. The rates heavily depend on the mode share patterns prevalent at the study locations, and more importantly – since many studies are not based on representative samples - in study participants' travel patterns. For example, in places with low public transport rates, few such trips will shift to E-biking. Similarly, subjects that mostly travel by car will likely have a higher substitution rate of car trips.

[28]See `https://www.thelocal.ch/20150616/zurich-voters-back-bike-lane-expansion-plan?`
[29]See `https://www.bern.ch/velohauptstadt/velo-offensive/ziel?`

As described in the methods section, research has taken two distinct approaches in assessing substitution rates. Cross-sectional studies of E-bikers, such as ours, build on the advantage of being able to recruit relatively large samples, bolstering the estimates with statistical power, but undermining such gains with challenges in retrospectively assessing mode substitution. A meta-analysis of 24 such studies put median substitution rates at 27% for cycling, 33% for public transport, 10% for walking, and 24% for driving, with large variation across studies (Bigazzi and Wong, 2020). In contrast, longitudinal (before-after) studies typically take advantage of planned interventions which encourage or subsidize E-bike purchase either as experiments with control group, or quasi-experimental (or "natural experiments") without control group. While these studies allow direct observation of change in travel behavior (i.e. substitution), they are often hampered by limited and skewed samples not representing the general (E-biking) population. A recent meta-analysis confirms these concerns, identifying only ten studies of longitudinal design, less than half of which including samples of more than 100 E-bikers, among other limitations (Chevance et al., 2025). In contrast to our study and other cross-sectional findings, this meta-analysis reports considerably higher substitution of driving, which can at least in part be explained by the focus on frequently driving study participants in some studies. Our study contributes a unique approach addressing some key limitations prevalent in the current designs. Namely, our design invests heavily in reducing recall bias when asking participants about substitution, removing the variation introduced by (typically unknown) trip length, purpose, and "averaging of typical trips". It further weighs the opportunistic EBIS sample with a representative national household travel survey, correcting for the fact that our "mix" of E-bikers differs from the one in Switzerland. As such, when calculating emission effects, we need to assume that Swiss E-bikers substitute in similar ways as our participants, once trip distance, purpose, individual characteristics, and E-bike type are controlled for. However, the non-representative distribution of these attributes in our sample does not distort our findings (e.g., the fact that in EBIS regular E-bikes and fast S-pedelecs split almost 50:50, whereas in reality the ratio is closer to 80:20). Last, our sample size of almost 1600 E-bikers is unmatched by any other study except one Dutch panel study, which followed 11'000 E-bikers over four years. (17% of participants in this representative sample own an E-bike, compared to 1% in Switzerland) (de Haas et al., 2021).

Nevertheless, there are at least two methodological aspects that may lead to some bias. Our sample is skewed towards large agglomerations, which were the focus of some but not all of our recruitment efforts. As such, substitution behavior of "rural" E-bikers – for example a possibly greater substitution of driving – may be underrepresented in our estimates. And second, the trips presented in the retrospective survey were required to be of at least 2 km in length, and they were selected to present "unique" trips. This assured capturing substitution information for as many distinct trips as possible. With further analysis, the frequency/repetition of trips could be extracted from the tracking data and the trips weighted accordingly.

Overall, it is fair to say that by current standards, our findings provide robust estimates of substitution behavior among Swiss E-bikers, clearly indicating that E-bikes substitute for conventional cycling, public transport, and driving, while shifting walking trips is very rare.

To put our findings into (international) perspective, the relatively high mode share of public transport (12%) and the relatively low share of driving (<40%) [30] need to be taken into account.

Exploring the future potential for emission reductions through various hypothetical scenarios, we find that reductions of transport-related emissions in the range of 0.4-1.3% are within reach for moderate scenarios, whereas more ambitious scenarios are required to increase this figure.

As is state-of-the-art with such scenario calculations, our study cannot assess how easily (or not) the various scenarios could be achieved, and through which measures. While current trends may reach levels assessed in the moderate scenarios within a time frame of years, international comparisons - specifically with the high mark set by the Netherlands (Huang et al., 2024) [31] - indicate that substantial and systematic investments into cycling infrastructure and safety[32], accompanied by de-incentivization of private motorized transport could indeed result in substantially higher uptake of E-biking closer to some of our more ambitious scenarios.

[30]National estimates, trip/stage-based: Walking: 41.5%, Cycling: 5.2%, Regular E-bikes: 0.8%, S-pedelecs: 0.3%, Public transport: 12%, Motorized private transport: 38%. Source BFS (2023)

[31]While comparisons to high levels of conventional cycling in the Netherlands are often confronted with skepticism in Switzerland due to the famously hillier terrain, this concern is moot in the context of E-biking

[32]ETH's E-Bike City project provides compelling visualizations of how such redesigned urban spaces could look like (https://ebikecity.baug.ethz.ch/en/)

7 Conclusions

In this project we build up a panel of E-bikers and conventional cyclists and track them via a GPS-based smartphone app. Our panel makes contributions to the literature on tracking-based mobility studies, particularly RCTs and studies focusing on cyclists and E-bikers. To our knowledge, EBIS is the largest tracking data set of E-bikers and cyclists worldwide, with 3'940 participants tracked and 324 thousand user-days. A new algorithm for aggregating GPS tracks into origin-destination trips produces more accurate information on travel behavior. High participant engagement in EBIS is a promising sign for future tracking studies; a majority of participants willingly contributed their mobility data for weeks past the official study end. However, recruiting samples representative of the target study population is not without challenges; these challenges would be exacerbated in places where E-biking is a less established mode of transport. Even after weighting the sample to be more representative of Swiss bicycle and E-bike owners, EBIS participants differ in their travel behavior, traveling further and more often. Nonetheless, the EBIS dataset with over a half-million E-bike and bicycle tracks spread across both urban and rural spatial typologies provides a wealth of data for new research on carbon emissions from E-biking; the potential for financial incentives to maximise the potential of E-biking; and the similarities and differences between cyclists and E-bikers with regards to travel behavior and cycling infrastructure preferences.

Based on the data generated within the tracking sample, the project follows three lines of inquiry. Section 4 investigates the determinants for route choice among cyclists, which are valuable parameters for regional transport models. The analysis of **revealed preferences for route choice** highlights several key factors that influence how cyclists navigate urban agglomerations. The most significant preference is for shorter travel distances, indicating a strong tendency toward efficiency in route selection. Slope also plays an important role, with cyclists generally avoiding routes with steep inclines. Infrastructure type significantly affects preferences as well, with bike lanes being notably favored over bike paths, shared lanes, and streets without dedicated cycling infrastructure. Motorized traffic volume emerges as a strong deterrent, while the presence of traffic lights and lower posted speed limits have a more nuanced or limited impact. Additionally, the study reveals that these preferences are not uniform across all cyclists; age, bike type, and gender can shape how different individuals respond to various route attributes. These findings underscore the multifaceted nature of cycling behavior and highlight the importance of designing urban environments that account for both physical conditions and diverse user needs.

We increased our sampling density for the urban areas in Zurich, Aarau, and Basel. In all cities, shorter routes and gentle gradients are generally preferred, while steep slopes and heavy motorized traffic are seen as deterrents. Aarau cyclists show a clear preference for bike lanes over other types of cycling infrastructure, in contrast to Basel, where bike paths are favored, and Zurich, where mixed bike paths are more appreciated. Interestingly, Aarau cyclists appear less concerned with motor vehicle speed limits than those in Zurich and Basel, potentially reflecting a different traffic context or rider composition. The inclusion of interaction effects in Aarau's model also highlights how preferences vary across age groups and bike types, underscoring the importance of considering user diversity in infrastructure planning. Overall, these findings emphasize that cycling preferences are context-dependent and suggest that local infrastructure planning should be tailored to the specific needs and behaviors of cyclists in each city.

The **stated-preference study on route choice** focuses more closely on the attributes of bicycle infrastructure. It confirms that wide, dedicated cycling paths offer the highest level of both subjective and objective safety, making them the most preferred cycling infrastructure—especially among non-cycling females. This group, which currently cycles the least, should be prioritized in cycling policy efforts. Although cycling paths are most valued, well-designed neighborhood streets—especially those without parked cars or car traffic and enhanced with bike-friendly features—can achieve similar levels of attractiveness. In some cases, they are even preferred over main streets with cycling lanes. Preferences for cycling infrastructure vary significantly across user groups, influenced by gender, cycling frequency, and bike type. Notably, S-pedelec riders value cycling infrastructure less, as their speed and acceleration capabilities align more closely with car traffic. Still, most prefer dedicated paths when available. Physical separation methods like bollards offer limited perceived safety improvements and may even be counterproductive for some. In contrast, UFO-style separators are generally favored due to their flexibility and lower collision risk. Gender differences also reveal that infrastructure quality is a greater deterrent for women than for men, implying that improved infrastructure could increase female participation in cycling more significantly. Finally, while some willingness-to-pay (WTP) values reported are unrealistically high, they highlight relative preferences rather than literal trade-offs. This part of the suggests refining experimental design in future research, including using real trip data for more accurate modeling.

The project also included a **randomized controlled trial** (RCT) for a subset of the participants. This field experiment provides clear evidence that pricing transportation based on its true societal costs—known as a Pigovian tax—can lead to meaningful reductions in traffic-related externalities like pollution, congestion, and public health burdens. By financially rewarding sustainable choices, such as E-biking and walking, we observed a 6.9 % drop in the negative side effects of travel, with no significant reduction in overall mobility. Participants reduced car use by over 8% and increased cycling and walking substantially, particularly when they had access to faster E-bikes (S-pedelecs). Our results show that relatively small financial incentives—aligned with the environmental and health impacts of each transport mode—can lead people to shift from cars to more sustainable options. In effect, the participants traveled more responsibly without sacrificing convenience or freedom of movement.

Policymakers should take note of three key takeaways. First, E-bikes are powerful car substitutes. Faster models especially offer real alternatives for daily travel, and policy frameworks should support their broader adoption through infrastructure, regulation, and incentives. Second, transport pricing works. By implementing a price on the societal costs of travel, the study found that individuals made more sustainable transport choices. Participants not only changed how they traveled, but when they traveled—shifting away from congested periods. This can reduce traffic stress and improve system-wide efficiency without requiring heavy-handed restrictions. Ultimately, while full-scale Pigovian pricing may be politically challenging, the principles behind it can inform a range of practical policy tools: congestion charges, E-bike subsidies, peak-time public transport discounts, and more. These tools can make cities cleaner, quieter, and more livable—while empowering individuals to make better travel decisions.

The last part of the project focuses on the **carbon savings from E-biking**. This not only depends on the share of this relatively new mode of transport, but also on what modes it substitutes. We find that E-biking in Switzerland substitutes for conventional cycling, public transport, and driving to approximately equal parts. The emission reductions by current (meaning 2021) levels of E-biking are relatively small, compared to total emissions of land transport, at 0.17% (22'441 tons). Nevertheless, the average E-bike trip reduces emissions by 78%, compared to the prior mode used for that same trip, and current E-bikers reduce their personal transport-related carbon footprint by 18%. Systematic prioritization of E-biking and other sustainable modes, as already achieved in, e.g., the Netherlands, could potentially yield much more substantial reductions, with CO_2 reductions attributable to E-biking in the range of 2-10% of total ground transportation.

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Appendices

A Additional tables and figures

A.1 Randomized controlled trial

A.1.1 Identification strategy

A canonical test for the common trends assumption involves comparing the linear trends of the control and treatment groups prior to treatment. The regressions presented below include only days within the observation period. The absence of a significant "Treated x Study day" interaction term supports the assumption of parallel (linear) trends between the two groups.

Table A.1: Common pre-treatment linear trends in distances

	(1) Total distance	(2) Car	(3) Public transport	(4) E-Bike	(5) Walking
Treated	-0.497	-1.100	0.671	-0.163	0.141
	(1.851)	(1.540)	(1.152)	(0.428)	(0.097)
Study day	-0.012	-0.065	0.026	0.049**	-0.003
	(0.082)	(0.076)	(0.043)	(0.019)	(0.004)
Treated × Study day	-0.044	-0.052	-0.001	0.007	-0.001
	(0.078)	(0.071)	(0.045)	(0.016)	(0.004)
adj. R^2	0.005	0.013	0.001	0.075	0.009
Clusters	1’084	1’084	1’084	1’084	1’084
N	27’147	27’147	27’147	27’147	27’147

Notes: * p<0.05, ** p<0.01, *** p<0.001. Standard errors (in parentheses) are clustered at the participant level. All regressions are based solely on pre-treatment data and include date fixed effects.

Table A.2: Common pre-treatment linear trends in external costs

	(1) Total Ext.	(2) Environm. Ext.	(3) Congest. Ext.	(4) Health Ext.	(5) Accid. Ext.
Treated	-0.122	-0.038	-0.011	-0.035	-0.038
	(0.197)	(0.053)	(0.043)	(0.102)	(0.068)
Study day	-0.008	-0.000	0.001	-0.011*	0.002
	(0.010)	(0.003)	(0.002)	(0.005)	(0.003)
Treated × Study day	-0.004	-0.001	-0.001	-0.002	0.001
	(0.009)	(0.002)	(0.002)	(0.004)	(0.003)
adj. R^2	0.010	0.008	0.009	0.037	0.035
Clusters	1’084	1’084	1’084	1’084	1’084
N	27’147	27’147	27’147	27’147	27’147

Notes: * p<0.05, ** p<0.01, *** p<0.001. Standard errors (in parentheses) are clustered at the participant level. All regressions are based solely on pre-treatment data and include date fixed effects.

A.1.2 Tracking accuracy and strategic corrections

Tracking accuracy Participants had the option to correct the automatically detected travel mode. Figure A.1 displays the confusion matrix comparing the automatically detected modes with the corrections, for confirmed trip stages from non-treated individuals only. The tracking app did not automatically detect certain modes such as boats or cablecars, resulting in a higher number of corrected modes.

Figure A.1: Confusion matrix of mode detection

Corrected Mode

Detected Mode	Airplane	Boat	Bus	Cablecar	Car	CarsharingMobility	Ebicycle	Escooter	Etrottinett	LightRail	Motorbike	RegionalTrain	RidepoolingPikmi	Scooter	Ski	Subway	TaxiUber	Train	Tram	Walk
Airplane	100	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Bus	0	0	61.8	0	32.3	0.1	3.5	0	0	0.1	0.2	0	0	0.2	0	0	0.1	0.1	0.3	1.2
Car	0	0.1	0.9	0.5	93.6	0.1	2.2	0.1	0	0.4	0.4	0.1	0	0.4	0.3	0	0.1	0.4	0.2	0.2
Ebicycle	0	0.2	0.1	0.2	0.6	0	95.6	0	0.1	0	0.3	0	0	0.3	1.1	0	0	0	0	1.3
LightRail	0	0	0.4	0	4	0	0.2	0	0	92.1	0	0.6	0	0	0	0.2	0	2.1	0.1	0.1
RegionalTrain	0	0.3	0	0	11.4	0	0.3	0	0	1.3	0	83.1	0	0	0	0	0	3.6	0	0
Subway	0	0	0	0	4.3	0	4.7	0	0	0	0	0	0	0	0	89.3	0	0.4	0	1.2
Train	0	0.1	0.5	0.2	12.8	0	0.6	0	0	3.5	0	0.3	0	0.1	0	0	0.2	81.4	0.2	0.1
Tram	0	0	0.3	0	1.4	0	0.5	0	0	0	0	0	0	0	0	0	0	0	97.4	0.4
Walk	0	0.1	0.1	0.1	0.9	0	1.4	0	0	0	0	0	0	0	0.2	0	0	0	0	97.1

Note: Confusion matrix for mode detection among confirmed trip stages. The values represent the percentage shares relative to the total number of stages classified as each respective mode.

The confusion matrix demonstrates exceptionally high hit rates for most modes, with values generally exceeding 90%. However, the mode detection algorithm exhibits notable challenges in distinguishing bus trips from car trips, with 32.3% of bus trips being misclassified as car trips. A similar issue arises in the detection of (regional) train trips, albeit to a much lesser extent.

Strategic corrections The results of our study reaffirm that individuals respond to financial incentives. This raises the possibility that some treated participants may have adjusted their tracking diaries to maximize their financial rewards from the study. Such strategic modifications, diverging from genuine corrections as illustrated in Figure A.1, pose a threat to the internal validity of our findings and must be carefully examined. Our study design presents two potential avenues for participants to manipulate their behavior to maximize financial rewards. First, by falsely altering the detected travel mode to one associated with lower external costs. Second, by deactivating GPS tracking during trips with higher costs. Notably, the tracking app does not allow users to modify recorded GPS points or manually add trips. This design effectively minimizes the risk of manipulation, as only directly observed trips are included in the analysis. Both concerns can be addressed by analyzing the enriched GPS tracks. To assess the likelihood of untruthful corrections, we conduct a series of DiD regressions, replicating the main ATE regressions, using the percentage of corrected tracks per person-day as the outcome variable. These outcomes are expected to remain relatively stable before and after treatment, as they are not influenced by changes such as a reduction in car trips resulting from the treatment. Cheating behavior among treated individuals would be indicated by a significantly higher correction percentage during the treatment period. As shown by column (1) in Table A.3, no such pattern is observed. However, the mode-specific regressions in columns (3) and (4) reveal a significantly higher correction percentage away from car trips and, to a lesser extent, towards walking. Column (3) shows that participants in the treatment group correct 3.5 percentage points more car trips during the treatment period compared to the control group (11.9% vs. 8.4%). Column (5) shows no significant difference in the percentage of tracks marked as "completely misdetected" by participants. To investigate strategic fiddling through GPS deactivation, we examine the geographic distance between the final GPS point of one stage and the initial point of the subsequent stage, even if interrupted by a stay. Had treated individuals attempted to reduce external costs using this strategy, a significant difference in these distances should be observed. However, column (6) reveals no such evidence.

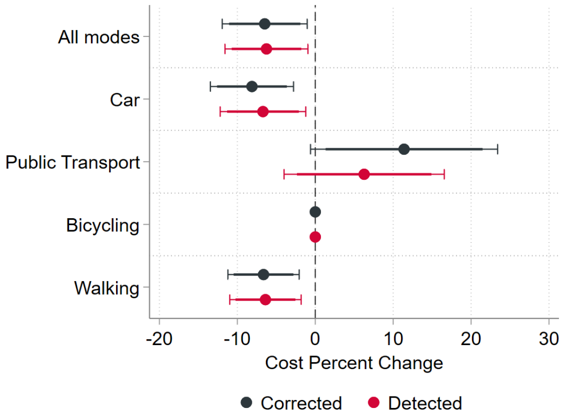
Table A.3: Regressions to detect cheating behavior

	Corrections					
	Overall (%) (1)	To car (%) (2)	From car (%) (3)	To walking (%) (4)	Deletions (%) (5)	Spatial jumps (km) (6)
Treated	0.296	-0.261	3.498***	0.166*	0.090	1.381
	(0.280)	(0.384)	(0.635)	(0.078)	(0.175)	(1.037)
adj. R^2	0.172	0.207	0.201	0.131	0.220	0.019
Clusters	1'085	1'085	1'085	1'085	1'085	1'085
N	57'814	36'867	38'969	50'735	57'814	61'410

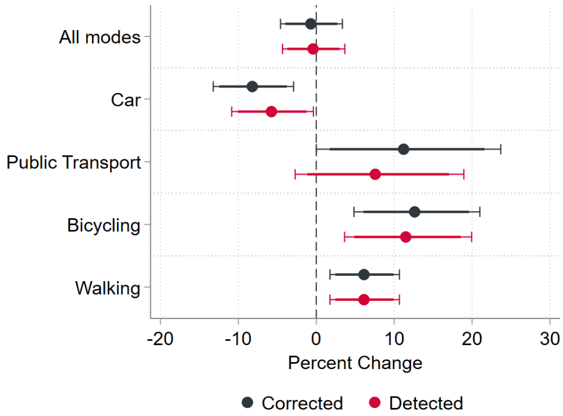
Notes: * $p<0.05$, ** $p<0.01$, *** $p<0.001$. Standard errors (in parentheses) are clustered at the participant level. For columns (1)–(5), the outcome variable is defined as the percentage (%) of corrected tracks among all tracks of the respective mode on a given day. Cheating behavior among treated individuals might be indicated by a significantly higher correction percentage during the treatment period. The coefficients represent differences in percentage points. Column (5) examines the percentage of tracks marked as "completely misdetected". The outcome in column (6) is the total daily distance of spatial gaps (as the crow flies) in the GPS data.

The observed increase in corrections away from cars may suggest some degree of strategic behavior among treated individuals. However, it could just as easily reflect that treated participants put in more effort due to the larger financial incentive, leading to a higher correction rate. Fortunately, the comprehensive tracking data enables us to analyze raw, uncorrected data alongside corrected data. Using raw tracking data, based solely on automatically detected modes, eliminates any potential strategic reporting but also disregards genuine corrections by participants. The true effect of the experiment likely lies between these two data versions. Figure A.2 compares the results of our main ATE regressions using corrected and raw data. The comparison shows only minor differences, with no impact on the 5% significance level of the regressions, except for the ATE on public transport distance.

Figure A.2: Comparison of ATEs with and without corrections



(a) External costs



(b) Distance

Notes: Comparison of the treatment effects accounting for participant corrections (black) versus the effects when all corrections are disregarded (red). The thick bars represent 90% confidence intervals, while the thin bars indicate 95% confidence intervals.

A.1.3 Differential attrition and observability

Differential attrition, where participants systematically drop out of a study based on treatment status or outcome variables, poses a key concern in field experiments (Ghanem et al., 2023). To address this concern, we conduct a determinants-of-attrition test to verify that attrition in our study is not systematically related to treatment assignment or key outcomes. To assess attrition, we define a variable that measures the number of days an individual was observable (i.e., provided a valid tracking day) during each study period. This measure is normalized by dividing it by the total possible observable days for each individual: at least 28 days for the baseline and 35 days for the treatment period. We estimate regressions for two outcome variables, "Observable (days)" and "Observable (%)", with results presented in Table A.4. The explanatory variables include study group assignment, as well as the individual's average baseline values for the main outcome variables, "external costs" and "car distance".

Table A.4: Determinants-of-attrition test

	External costs			Car distance		
	Observable (days)	Observable (%)		Observable (days)	Observable (%)	
	(1)	(2)	(3)	(4)	(5)	(6)
Treated	0.242	0.007	0.007	0.231	0.007	0.007
	(0.350)	(0.010)	(0.010)	(0.350)	(0.010)	(0.010)
Avg. baseline external costs	−0.144	−0.004	−0.003			
	(0.077)	(0.002)	(0.002)			
Baseline observability (%)			0.319***			0.318***
			(0.031)			(0.031)
Avg. baseline car distance				−0.019*	−0.001*	−0.0003
				(0.009)	(0.0003)	(0.0003)
Constant	31.889***	0.911***	0.643***	31.919***	0.912***	0.644***
	(0.370)	(0.011)	(0.028)	(0.366)	(0.010)	(0.028)
Adjusted R^2	0.002	0.002	0.092	0.002	0.002	0.092
N	1'085	1'085	1'085	1'085	1'085	1'085

Notes: * $p<0.05$, ** $p<0.01$, *** $p<0.001$. Standard errors in parentheses. The table presents regressions for two outcome variables, "Observable (days)" and "Observable (%)". Observability is defined as the number of days an individual provided valid tracking data during each study period, normalized by the total possible observable days: at least 28 days for the baseline period and 35 days for the treatment period. Explanatory variables include study group assignment and the individual's average baseline values for the main outcome variables, "external costs" and "car distance".

The table reveals no significant differences in observability across treatment groups in any of the regressions. Furthermore, we do not find any relationship between baseline total external costs and the observability measures. However, a correlation does emerge between average baseline car distances and observability in the treatment period, depicted in columns (4) and (5). This relationship vanishes once we control for baseline observability as in column (6). Based on these findings, we conclude that there is no evidence of differential attrition in our study, reinforcing the internal validity of our main results.

A.1.4 Weather controls

Weather conditions significantly influence mode choice, particularly for active transport modes (Böcker et al., 2016). However, in our DiD framework, such factors should not bias the results. The random assignment to treatment or control groups ensures that weather effects are balanced across groups, thereby minimizing their influence on the estimated treatment effects. This assumption holds more robustly with larger sample sizes. Given our finite sample size, we augment the tracking data with high-resolution weather information from MeteoSwiss, including temperature and precipitation (in mm/h) at a 1 x 1 km spatial resolution. Following the methodology of Hintermann et al. (2025), we include temperature in two forms to account for the distinct effects of unusually hot and cool days:

$$\text{Heat}_{jt} = \max\{t_{jt}^{max} - 25,\, 0\}$$
$$\text{Cold}_{jt} = \max\{7 - t_{jt}^{min},\, 0\}$$

where t_{jt}^{max} and t_{jt}^{min} denote the daily maximum and minimum temperatures, respectively, at the location where a trip begins. For each trip j, these variables capture the positive deviations of daily temperature above 25 (heat) and below 7 (cold) degrees Celsius. Heat, cold and precipitation averages are then computed across all trips made by individual i on date t. On valid tracking days with no recorded trips, we use weather conditions at the last recorded location to impute values. Table A.5 reports the main regression results for distances traveled, incorporating these weather controls.

Table A.5: ATE of distances controlling for weather

	(1) Total distance	(2) Car	(3) Public transport	(4) E-Bike	(5) Walking
Treated	-0.219	-1.926**	0.961	0.572**	0.119**
	(0.861)	(0.734)	(0.529)	(0.179)	(0.041)
Heat day	-4.554**	-1.258	-2.267***	-0.263	-0.148*
	(1.580)	(1.257)	(0.687)	(0.336)	(0.066)
Cold day	-0.099	-0.011	-0.095*	0.004	-0.001
	(0.085)	(0.071)	(0.046)	(0.012)	(0.004)
Precipitation	-0.061	0.002	-0.004	-0.043***	-0.015***
	(0.088)	(0.076)	(0.049)	(0.012)	(0.004)
adj. R^2	0.126	0.124	0.136	0.319	0.203
Clusters	1’085	1’085	1’085	1’085	1’085
N	61’410	61’410	61’410	61’410	61’410

Notes: * p<0.05, ** p<0.01, *** p<0.001. The dependent variable contains the distance traveled including zeroes aggregated to the person-day level. The coefficients show the ATE in kilometers. “Heat day” and “Cold day” capture the positive deviations of daily temperature above 25 (heat) and below 7 (cold) degrees Celsius. Standard errors (in parentheses) are clustered at the participant level. All regressions include person and date fixed effects, as well as a dummy variable indicating days following the receipt of a negative travel budget in the mobility report.

Including weather controls neither improves the precision nor alters the magnitude of the treatment effect estimates. While cold temperatures show minimal impact on daily transport behavior, precipitation significantly decreases active mode distances, and heat reduces daily distances traveled by 4.5 km per degree above 25 degrees. Heat also reduces the use of public transport and walking. Alternative specifications, such as dummy variables for extreme temperatures, similarly did not affect the significance or magnitude of the treatment effects. Controlling for weather in regressions on external costs, as shown in Table A.6, likewise yields no improvements in precision.

Table A.6: ATE of external costs controlling for weather

	(1) Total Ext.	(2) Environm. Ext.	(3) Congest. Ext.	(4) Health Benefits	(5) Health Costs	(6) Accid. Ext.
Treated	-0.210*	-0.048	-0.068***	0.106***	-0.042	0.054
	(0.091)	(0.025)	(0.020)	(0.026)	(0.032)	(0.029)
Heat day	-0.401	-0.088	-0.019	-0.066	-0.190	-0.169*
	(0.237)	(0.046)	(0.028)	(0.046)	(0.104)	(0.085)
Cold day	-0.005	-0.001	-0.002	0.000	-0.002	0.001
	(0.009)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Precipitation	0.001	-0.001	-0.000	-0.009***	-0.000	-0.007***
	(0.009)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)
adj. R^2	0.116	0.127	0.114	0.324	0.115	0.222
Clusters	1’085	1’085	1’085	1’085	1’085	1’085
N	61’410	61’410	61’410	61’410	61’410	61’410

Notes: * p<0.05, ** p<0.01, *** p<0.001. The dependent variable is the external cost of transport (in CHF) aggregated to the person-day level. “Heat day” and “Cold day” capture the positive deviations of daily temperature above 25 (heat) and below 7 (cold) degrees Celsius. Standard errors (in parentheses) are clustered at the participant level. All regressions include person and date fixed effects, in addition to a dummy marking days after reception of a negative travel budget in the mobility report.

A.1.5 Multivariate regressions

Table A.7: Multivariate interactions: External costs

	(1) Environm. Ext.	(2) Congest. Ext.	(3) Health Benefits	(4) Health Costs	(5) Accid. Ext.
Treated	0.047	0.078	0.069	0.054	0.067
	(0.068)	(0.089)	(0.086)	(0.079)	(0.060)
Treated x Male=1	-0.046	-0.078	-0.026	-0.057	-0.030
	(0.036)	(0.055)	(0.039)	(0.042)	(0.030)
Treated x Age>=50	-0.065	-0.076	-0.042	-0.074	-0.069*
	(0.040)	(0.055)	(0.042)	(0.045)	(0.030)
Treated x Tertiary educ.=1	0.010	0.006	-0.036	0.016	-0.028
	(0.040)	(0.053)	(0.043)	(0.046)	(0.034)
Treated x HH size<3	-0.012	-0.031	0.014	-0.016	0.002
	(0.040)	(0.055)	(0.044)	(0.046)	(0.034)
Treated x French=1	0.036	-0.014	-0.036	0.068	0.039
	(0.056)	(0.077)	(0.053)	(0.059)	(0.044)
Treated x Urban=1	-0.028	-0.082	0.090*	-0.054	0.010
	(0.036)	(0.048)	(0.039)	(0.041)	(0.030)
Treated x PT reduction=1	0.007	0.015	0.017	0.035	0.020
	(0.045)	(0.058)	(0.051)	(0.051)	(0.036)
Treated x S-pedelec=1	-0.045	-0.084	0.065	-0.043	0.054
	(0.040)	(0.055)	(0.038)	(0.047)	(0.032)
Pseudo R^2	0.104	0.131	0.219	0.114	0.130
Clusters	1’085	1’085	1’085	1’085	1’085
N	61’410	61’410	61’410	61’410	61’410

Notes: * $p<0.05$, ** $p<0.01$, *** $p<0.001$. The dependent variable is the external cost of transport (in CHF) aggregated to the person-day level. All dimensions include one omitted category. *Treated* is thus associated with an observation that has a zero for all included dummies. The coefficients were estimated using a PPML model, and the results show proportional effects. Standard errors (in parentheses) are clustered at the participant level. All regressions include date and person fixed effects.

A.2 Carbon emission reductions attributable to E-biking

A.2.1 CO2 emission factors from MOBITOOL used in EBIS

Table A.8: CO2 Emission Factors (g/km)

Mode of transport	Fuel type	Category	CO2 (g/km)
Suburban/regional train	Electricity mix SBB	Regional transport, incl. S-Bahn	8.04
Local public transport	-	Local bus or tram	25.42
E-bike	Electricity	25 km/h	11.33
		45 km/h	9.81
Bicycle	NA	Conventional, inner-city	5.58
Motorcycle	Gasoline	Average size	163.64
Passenger cars	Electricity	Average size	89.79
		Large	91.02
		Large SUV	105.65
		Compact	59.92
		Mid-size	69.70
	Gasoline	Average size	185.99
		Large	200.41
		Large SUV	233.02
		Compact	129.68
		Mid-size	150.62
	Diesel	Average size	188.97
		Large	175.75
		Large SUV	210.63
		Compact	110.87
		Mid-size	132.21
	Hybrid-Gasoline	Large	178.54
		Large SUV	206.95
		Compact	118.24
		Mid-size	139.67
	Fleet average	Average size	186.43

Table A.9: Percentage of Substituted Modes by E-bike Category

Substituted mode	E-bike (25 km/h) (N = 2625)	E-bike (45 km/h) (N = 3486)
Bicycle (without electric assist)	42%	34%
Local bus or tram	24%	15%
Car	22%	28%
Suburban/regional train	5%	12%
Walking	3%	1%
Other	2%	3%
Motorcycle	1%	2%
E-bike (45 km/h)	0%	n.a.
E-bike (25 km/h)	n.a.	3%
New trip	n.a.	2%

A.2.2 Mode substitution rates in EBIS

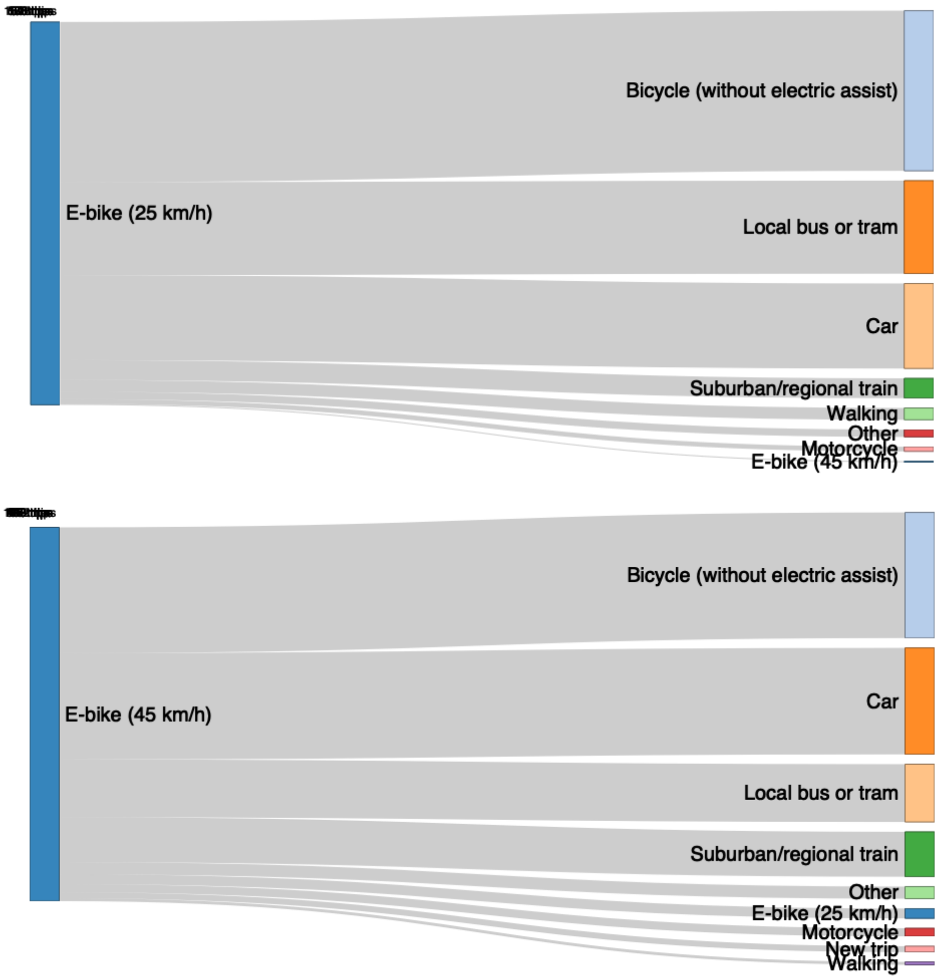


Figure A.3: Substitution rates (Sankey plot); see Table A.9 for values.

A.2.3 Carbon emission reductions: Status quo

Tables below show baseline net CO_2 savings using three different approaches to aggregate emission reductions factors derived from EBIS data.[33]

Nationwide totals:

Table A.10: CO_2 reductions attributable to Status Quo (2021), nationwide total (tons)

	Scenario	Total CO2 Reduction Nationwide	Total Reference CO2 Nationwide	Percent Change Total Nationwide
E-bike trips only	Status quo (2021)	-34,419	43,293	-79.50
All trips by E-bikers	Status quo (2021)	-34,419	139,796	-24.62
Trips 10km	Status quo (2021)	-17,793	2,301,706	-0.77
Large Agglo's	Status quo (2021)	-19,701	7,719,423	-0.26
All trips	Status quo (2021)	-34,419	13,156,436	-0.26

Note: ERF type: all.

Table A.11: CO_2 reductions attributable to Status Quo (2021), nationwide total (tons)

	Scenario	Total CO2 Reduction Nationwide	Total Reference CO2 Nationwide	Percent Change Total Nationwide
E-bike trips only	Status quo (2021)	-34,511	43,385	-79.55
All trips by E-bikers	Status quo (2021)	-34,511	139,887	-24.67
Trips 10km	Status quo (2021)	-17,765	2,301,677	-0.77
Large Agglo's	Status quo (2021)	-19,842	7,719,564	-0.26
All trips	Status quo (2021)	-34,511	13,156,527	-0.26

Note: ERF type: ebiketype.

Trip averages:

A.2.4 Carbon emission reductions: Scenarios

Tables below show scenario net CO_2 savings using three different reference datasets. Emission reduction factors used are based on stratified aggregation from EBIS data.

Nationwide totals:

Trip averages:

[33] (all = average; ebiketype = stratified by E-bike type; strata = stratified by agegroup, gender, E-bike type, and distance category)

Table A.12: CO_2 reductions attributable to Status Quo (2021), average trip (grams)

	Scenario	Mean CO2 Reduction per Trip	Mean Reference CO2 per Trip	Percent Change per Trip
E-bike trips only	Status quo (2021)	-769	969	-79.36
All trips by E-bikers	Status quo (2021)	-347	2,747	-12.63
Trips 10km	Status quo (2021)	-3	499	-0.60
Large Agglo’s	Status quo (2021)	-5	6,702	-0.07
All trips	Status quo (2021)	-5	6,670	-0.07

Note: ERF type: all.

Table A.13: CO_2 reductions attributable to Status Quo (2021), average trip (grams)

	Scenario	Mean CO2 Reduction per Trip	Mean Reference CO2 per Trip	Percent Change per Trip
E-bike trips only	Status quo (2021)	-761	961	-79.19
All trips by E-bikers	Status quo (2021)	-344	2,744	-12.54
Trips 10km	Status quo (2021)	-3	499	-0.60
Large Agglo’s	Status quo (2021)	-5	6,702	-0.07
All trips	Status quo (2021)	-5	6,669	-0.07

Note: ERF type: ebiketype.

Table A.14: CO_2 reductions attributable to Scenarios, nationwide (tons); (Reference dataset: Large_Agglos)

Scenario	Total CO2 Reduction Nationwide	Total Reference CO2 Nationwide	Percent Change Total Nationwide
Baseline	0	7,712,499	0.00
Status quo (2021)	-13,974	7,712,499	-0.18
Increase E-bike share 2-fold	-31,407	7,712,499	-0.41
Increase E-bike share 5-fold	-88,863	7,712,499	-1.15
Increase E-bike share 10-fold	-171,155	7,712,499	-2.22
Everyone like current E-bikers	-781,406	7,712,499	-10.13
Shift 10% of non-E-bike trips to E-bike	-117,413	7,712,499	-1.52
Shift 50% of non-E-bike trips to E-bike	-436,187	7,712,499	-5.66
Shift 50% of non-E-bike trips to E-bike, 50% cars electric	-327,698	6,134,645	-5.34
Shift 50% of non-E-bike trips of 5-10 km to E-bike	-350,411	7,712,499	-4.54
All trips by E-bike	-6,950,254	7,712,499	-90.12

Note: Reference dataset: Large_Agglos. ERF type: strata.

Table A.15: CO_2 reductions attributable to Scenarios, nationwide (tons); (Reference dataset: Trips_10km)

Scenario	Total CO2 Reduction Nationwide	Total Reference CO2 Nationwide	Percent Change Total Nationwide
Baseline	0	2,297,979	0.00
Status quo (2021)	-14,341	2,297,979	-0.62
Increase E-bike share 2-fold	-39,489	2,297,979	-1.72
Increase E-bike share 5-fold	-107,390	2,297,979	-4.67
Increase E-bike share 10-fold	-214,514	2,297,979	-9.33
Everyone like current E-bikers	-799,263	2,297,979	-34.78
Shift 10% of non-E-bike trips to E-bike	-99,055	2,297,979	-4.31
Shift 50% of non-E-bike trips to E-bike	-361,557	2,297,979	-15.73
Shift 50% of non-E-bike trips to E-bike, 50% cars electric	-291,438	1,844,389	-15.80
Shift 50% of non-E-bike trips of 5-10 km to E-bike	-617,966	2,297,979	-26.89
All trips by E-bike	-1,993,954	2,297,979	-86.77

Note: Reference dataset: Trips_10km. ERF type: strata.

Table A.16: CO_2 reductions attributable to Scenarios, average trip (grams); (Reference dataset: Large_Agglos)

Scenario	Mean CO2 Reduction per Trip	Mean Reference CO2 per Trip	Percent Change per Trip
Baseline	0	6,698	0.000
Status quo (2021)	-2	6,698	-0.030
Increase E-bike share 2-fold	-3	6,698	-0.045
Increase E-bike share 5-fold	-6	6,698	-0.090
Increase E-bike share 10-fold	-11	6,698	-0.164
Everyone like current E-bikers	-138	6,698	-2.060
Shift 10% of non-E-bike trips to E-bike	-16	6,698	-0.239
Shift 50% of non-E-bike trips to E-bike	-64	6,698	-0.956
Shift 50% of non-E-bike trips to E-bike, 50% cars electric	-47	5,355	-0.878
Shift 50% of non-E-bike trips of 5-10 km to E-bike	-38	6,698	-0.567
All trips by E-bike	-6,118	6,698	-91.341

Note: Reference dataset: Large_Agglos. ERF type: strata.

Table A.17: CO_2 reductions attributable to Scenarios, average trip (grams); (Reference dataset: Trips_10km)

Scenario	Mean CO2 Reduction per Trip	Mean Reference CO2 per Trip	Percent Change per Trip
Baseline	0	499	0.000
Status quo (2021)	-3	499	-0.601
Increase E-bike share 2-fold	-6	499	-1.202
Increase E-bike share 5-fold	-16	499	-3.206
Increase E-bike share 10-fold	-32	499	-6.413
Everyone like current E-bikers	-135	499	-27.054
Shift 10% of non-E-bike trips to E-bike	-15	499	-3.006
Shift 50% of non-E-bike trips to E-bike	-55	499	-11.022
Shift 50% of non-E-bike trips to E-bike, 50% cars electric	-45	399	-11.278
Shift 50% of non-E-bike trips of 5-10 km to E-bike	-170	499	-34.068
All trips by E-bike	-446	499	-89.379

Note: Reference dataset: Trips_10km. ERF type: strata.