The effect of shared e-scooter programs on modal shift: Evidence from Sweden

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Abstract

Fostering sustainable cities necessitates a significant paradigm shift from motorised vehicles to active mobility. To explore the potential of this transition, we polled 805 (non)users of e-scooters in Sweden via a survey to explore i) who e-scooter users are and ii) how e-scooter use affects the probability of modal substitution for users. The propensity score matching method was used to obtain unbiased estimates of e-scooter usage impact on modal substitution. We found that e-scooter users are more likely to have a high-paying job, a driving license, own e-bikes and cars, and public transport cards, suggesting diverse travel behaviours. These findings indicate that being an e-scooter user is associated with multimodal transport. Furthermore, being an e-scooter user will increase the probability of shifting their trip short range to an e-scooter by 46%. Findings provide pivotal insights into e-scooter modal shifts, crucial for ex-ante and ex-post evaluations of e-scooter adoption.

Keywords: electric scooter; modal substitution; transport planning; sustainable mobility
1. **Introduction**

Active mobility paves the way towards sustainable cities by addressing the challenges associated with motorised vehicles, such as noise and air pollution, traffic congestion, and by promoting an active lifestyle (Chibwe et al., 2021; Hosseinzadeh, Algomaiah, et al., 2021a; Lu et al., 2018; Patil et al., 2022). Active mobility primarily relies on cycling and walking; however, the challenges posed by steep terrain and long-distance travel can limit their applicability for certain trips (Abadi & Hurwitz, 2018; Kazemzadeh & Bansal, 2021a; Nikiforiadis et al., 2020). To address these limitations, powered micro-mobility options, including electric bikes (e-bikes) and electric scooters (e-scooters) have been introduced, expanding the range of active mobility choices, and overcoming challenges related to steep roads and relatively long-distance trips (Hosseinzadeh, Karimpour, et al., 2021; Zhou et al., 2023). Hence, to enhance the role of active mobility, it becomes essential to examine the contribution of powered micro-mobility, specifically e-scooters, in the context of active transport.

The introduction of e-scooters in 2017 has led to their rapid proliferation across more than 200 cities worldwide, with estimated market values reaching billions of dollars (McKenzie, 2020; Yang, Zheng, et al., 2022). In 2018, e-scooters accounted for the highest proportion of micro-mobility trips in the US, with 38.5 million recorded trips (Huo et al., 2021; Younes et al., 2020). Moreover, a similar trend of the increasing popularity of e-scooter usage has been observed in various European cities, further highlighting the common adoption of e-scooters as a mode of transport (Li et al., 2022). The popularity of e-scooters can be attributed to various factors, including their accessibility, relatively lax regulations, and the enjoyable experience of electrically assisted riding (Nikiforiadis et al., 2021). The rapid popularity and widespread adoption of e-scooters have presented challenges for local governments in formulating appropriate regulatory policies.
Initially, e-scooters were viewed favourably by governments as they appeared to promote ridership of active mobility options and alleviate traffic congestion (Weschke et al., 2022). However, issues such as traffic accidents, parking problems, and inconvenience for other road users have prompted governments to restrict the number of operators in certain cities or implement temporary e-scooter bans (Zou et al., 2020).

The introduction of e-scooters as a new mode of transport has significant implications for urban policies and infrastructure management (McKenzie, 2019). The utilisation of sidewalks and bike lanes by e-scooters impacts the capacity and configuration of the built environment (Nikiforiadis & Basbas, 2019). Moreover, the coexistence of various transport modes with different speeds and navigation characteristics can affect the safety and comfort of all road users, particularly vulnerable road users (Kazemzadeh & Bansal, 2021b). Additionally, e-scooters can influence users’ short- and long-term choices of transport modes, which in turn may impact supply-demand management. Consequently, the introduction of e-scooters can be regarded as an intervention, and it is crucial to assess the impact of their deployment to inform realistic planning and regulatory measures. By evaluating the characteristics of e-scooter users and non-users and assessing the impact of shared e-scooter systems on modal substitution, this study aims to provide valuable insights into user behaviour and the potential of e-scooters as an active transport option, contributing to a better understanding of the role they play in shaping urban mobility patterns and informing future policies.

1.1 Originality and scope of the paper

The existing literature on e-scooter mode choice has made significant progress in understanding various characteristics related to e-scooter adoption. However, a notable gap remains when it comes to establishing a clear baseline for assessing the extent of modal substitution between e-
scooter users and non-users. This limitation hinders our ability to accurately evaluate the true impact of e-scooter usage on modal shift. While studies have consistently identified distinct demographic characteristics of e-scooter users, such as being predominantly young, male, and having higher incomes, the absence of a control group for comparison makes it challenging to determine the precise magnitude of these differences.

To address this limitation and provide a more comprehensive understanding, our study introduces a control group and employs a rigorous methodology. By including both e-scooter users and non-users in our analysis, we can more effectively capture and compare their modal shift behaviours. This approach enables us to examine the unique impact of e-scooter usage on modal substitution while considering the demographic factors that differentiate users and non-users.

Our study offers three significant contributions. Firstly, we introduce a novel method by generating an artificial control group using Propensity Score Matching. This method allows us to account for confounding variables and obtain more accurate estimates of the actual impact of e-scooter usage on modal substitution. Secondly, we conduct a comprehensive analysis of e-scooter user characteristics, exploring how factors such as demographics, travel habits, and history may influence modal choices. By doing so, we uncover important insights into the specific mechanisms behind modal shifts. Lastly, our study focuses specifically on e-scooter usage in Sweden, considering the unique cultural, social, and economic factors that may influence modal choices in this Northern European context.

The rest of the paper is organised as follows: Section 2 provides an overview of the contextual literature. Section 3 presents data and the adopted method for this study. Results and discussions (Section 4) are in the penultimate section, and the conclusion (Section 5) ensues.
2. Literature review

In this section, we briefly discuss previous studies concerning 2.1) e-scooter usage characteristics, 2.2) the impact of e-scooters on modal shift, 2.3) the usage of e-scooters in Sweden, and 2.4) knowledge gaps and research needs. For a more comprehensive review of modal shift in e-scooters, we recommend referring to recent literature review studies conducted by (Wang et al., 2022) and (Kazemzadeh & Sprei, 2022).

2.1. E-scooter usage characteristics

The literature regarding the practice of e-scooter has rapidly increased since 2017, and several characteristics of this mode have been assessed (Hawa et al., 2021; Hosseinzadeh, Algomaiah, et al., 2021b). Understanding the usage pattern of e-scooters via assessing their trajectory (also open-source databases) is a dominant strand of e-scooter research (Caspi et al., 2020; Zuniga-Garcia et al., 2021). This research output sheds light on several factors, such as frequent paths, peak hours, usage distribution based on weather conditions and pick-up and drop-off locations (Almannaa et al., 2021; Noland, 2021). Moreover, the socio-demographic characteristics of e-scooters users via surveys have been frequently assessed (Laa & Leth, 2020; Mitra & Hess, 2021). Understanding the characteristics of e-scooter users and non-users contributes to better planning their travel demand (Reck et al., 2021). The overall trend of the previous literature demonstrates that male users are the dominant e-scooter riders (Aman et al., 2021; Nikiforiadis et al., 2021). Also, frequent users are mainly young adults with high levels of education (Cao et al., 2021; Laa & Leth, 2020; Reck & Axhausen, 2021). Despite the fact that previous research has examined the demographic characteristics of e-scooter users, such as gender and income, there is still a lack of knowledge about the travel habits, household structure, and travel preferences of e-scooter users (Badia & Jenelius, 2023).
2.2 The impact of e-scooters on modal shift

Understanding the role of e-scooters in modal supplement and substitution would contribute to supply and demand management (Nikiforiadis et al., 2023; Reck et al., 2022; Wang et al., 2022). The desired substitution scenario could be that e-scooters substitute trips conducted by private cars and consequently contribute to the sustainability agenda. However, in practice, e-scooter could also substitute and supplement cycling and walking, which are already desirable forms of transport.

E-scooters have frequently been referred to as a remedy for first-last-mile (short distance) trips; however, the literature yields mixed results: e-scooters could substitute and supplement both motorised and non-motorised transport modes (Reck & Axhausen, 2021). For instance, e-scooters are applicable for short-distance trips which supplement and substitute walking and cycling (Baek et al., 2021; Gössling, 2020). In contrast, e-scooters could also replace motorised vehicle trips such as public transport and cars in various contexts, specifically for short-distance trips and when individuals own an e-scooter (Bai & Jiao, 2020; Laa & Leth, 2020; Yan et al., 2023). To better understand the impact of e-scooter usage on transport mode selection, it might to use methodologies that take into consideration a broader range of user characteristics, such as their typical modes of transport, household composition, and their mobility patterns. Table 1 summarises previous research regarding the modal substitution of e-scooters.

2.3 The usage of e-scooter in Sweden

Shared e-scooters were first introduced in a few cities in Sweden in August 2018 and quickly spread throughout the country by September 2019, with the support of 10 active operators (DN, 2020). However, the number of e-scooter operators in Sweden has fluctuated since then, particularly during the COVID-19 pandemic. For example, in Stockholm, only two e-scooter operators (Tier and Voi) remained active in May 2020 during the outbreak of COVID-19, and the
rest withdrew their operations (Stigson et al., 2021). In Sweden, e-scooters are classified as bikes, and as a result, the rules that apply to bikes also apply to e-scooters. For example, users under the age of 15 are required to wear a helmet while using an e-scooter, and the operating speed of an e-scooter is limited to 20 km/h (Kazemzadeh et al., 2023).

The rapid popularity of e-scooters in Sweden has led to an increase in traffic safety issues. The first fatal accident involving an e-scooter occurred in May 2019, and there has been an increasing trend of accidents since the introduction of e-scooters (Stigson et al., 2021). Furthermore, e-scooters have caused several issues for other active mobility users in Sweden, such as improper parking on sidewalks and pedestrian threats. Additionally, there is a lack of information about the characteristics of e-scooter users, the impacts of modal substitution, and how providing shared e-scooter service may affect modal choice in Sweden. Such issues regarding the practice of e-scooters call for comprehensive research to evaluate the impact of e-scooter programs in Sweden.

2.4 Knowledge gaps and research needs

The literature has developed to understand the role of e-scooters in modal substitution and supplementation. However, several significant research gaps remain to be filled. First, there is a lack of research evaluating the impact of being a user of a new transport mode, such as e-scooters, on the decision of users to shift their current mode (the treatment impact on treated). This strand of research is vital in the supply and demand management of the transport sector. Second, from the methodological standpoint, there is a scarcity of research that has designed a "control group" in their study framework, which contributes to the internal validity of the research. Third, regardless of the rapid adoption of e-scooters in Northern European countries, research lags far behind the practice in evaluating the usage of e-scooters. Fourth, research is scarce on the characteristics of e-scooter users, including how active and mobile they are and their frequent
transport modes which help to predict whether e-scooters could replace cars or bikes. This study contributes to the body of the literature by exploring the impact of using e-scooters on modal shift, aiding authorities and planners in deploying new e-scooter schemes and regulating the current system. Moreover, this research is the first to provide information about both e-scooter users and non-users in the two largest Swedish cities, which have applications both internationally and in Nordic countries.
Table 1. Summary of previous studies regarding e-scooter modal substitution

<table>
<thead>
<tr>
<th>Author(s) (Year)</th>
<th>Location</th>
<th>Data/collection</th>
<th>Data analysis</th>
<th>Main conclusions or recommendations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Caspi et al. (2020)</td>
<td>The USA</td>
<td>Open-source databases</td>
<td>Descriptive statistics &amp; spatial econometrics</td>
<td>E-scooters could replace some leisure trips, and they could reduce car usage</td>
</tr>
<tr>
<td>Laa and Leth (2020)</td>
<td>Austria</td>
<td>Survey</td>
<td>Descriptive statistics</td>
<td>E-scooter mainly substitute walking and public transport, and e-scooter owners demonstrate the shift from personal cars</td>
</tr>
<tr>
<td>Kopplin et al. (2021)</td>
<td>Germany</td>
<td>Survey</td>
<td>Structural equation modelling</td>
<td>E-scooters mainly substitute walking rather than other transport modes</td>
</tr>
<tr>
<td>Baek et al. (2021)</td>
<td>Korea</td>
<td>Stated preference experiment</td>
<td>Logit models</td>
<td>It could be expected that e-scooters substitute some town bus trips</td>
</tr>
<tr>
<td>Bai et al. (2021)</td>
<td>The USA</td>
<td>Open-source databases</td>
<td>Difference-in-Differences regression modelling</td>
<td>Scooter use was minor in terms of overall leisure activity growth in Austin, Texas</td>
</tr>
<tr>
<td>Guo and Zhang (2021)</td>
<td>The USA</td>
<td>Survey</td>
<td>Mixed logit model</td>
<td>E-scooters could potentially compete with the taxi, lower cost, and leisure trip purposes</td>
</tr>
<tr>
<td>Lee et al. (2021)</td>
<td>The USA</td>
<td>Open-source databases (survey)</td>
<td>Regression model</td>
<td>E-scooters could substitute several modes, including carpool, bike, and taxi trips</td>
</tr>
<tr>
<td>Fearnley (2022)</td>
<td>Norway</td>
<td>Web survey</td>
<td>Regression</td>
<td>E-scooters could be a reliable substitution for walking during the daytime</td>
</tr>
<tr>
<td>Gebhardt et al. (2022)</td>
<td>Germany</td>
<td>German national household travel survey</td>
<td>Descriptive statistics</td>
<td>E-scooters could replace 13% of the daily car trips</td>
</tr>
<tr>
<td>Weschke et al. (2022)</td>
<td>Germany</td>
<td>Survey</td>
<td>Multinomial logit model</td>
<td>Shared e-scooter trips primarily replace walking, followed by public transport, and equally replace private bikes and cars</td>
</tr>
<tr>
<td>Asensio et al. (2022)</td>
<td>The USA</td>
<td>Natural experiment</td>
<td>Difference-in-Differences</td>
<td>Drivers face substantial increases in traffic congestion when scooters and e-bikes are banned, as many users return to passenger automobiles for last-mile travel</td>
</tr>
</tbody>
</table>
3. Methodology

The adopted methodology seeks to understand two related research questions:

RQ1) What variables (e.g., socio-demographic characteristics and travel habits) describe the probability of being an e-scooter user?

RQ2) How could being an e-scooter user affect users' probability of modal shift to an e-scooter?

The following sections present the methodology adopted to answer the research questions. Figure 1 represents the adopted methodology framework in this study based on survey data and propensity score matching.

![Diagram](Figure 1) The adopted methodology framework in this study (based on the Propensity Score Matching method)
3.1 Data collection

To elicit the preference of Swedish residents regarding using e-scooter, a stated-preference study was conducted. Based on an online survey, the respondents were asked about their socio-demographic characterises, travel history and habits, and potential preferences to replace their transport mode with an e-scooter. We created the survey by using the web-based Qualtrics platform. The survey was distributed via Dynata (a professional survey firm) in April 2022 on several survey panels in the two largest cities of Sweden, i.e., Stockholm and Gothenburg. We considered April for data collection as the weather is suitable for using an e-scooter in Sweden. Therefore, participants have fresh experience and memory regarding e-scooter usage.

The survey was written in Swedish and distributed to residents of Stockholm and Gothenburg aged 16 and over. 16 is the legal age threshold in Sweden to use e-scooters. We designed the survey with three blocks to capture participants' socio-demographic characteristics, travel history and habits, and modal substitution attitudes. To identify shared e-scooter users in the survey, we designed two questions in different sections. In doing so, we asked users if they had experience using e-scooter (Question 1) and if they had used e-scooters several times per day to never (Question 2) over the past few weeks.

We converted Question 2 into a binary response where 1 represents if the person uses e-scooters several times per day and 0 otherwise. If a person positively answered these two questions (responded 1 in Question 2), we categorised them as a user. After matching the response of participants from these two questions, we removed the record of those participants who contradicted these two questions. We also followed General Data Protection Regulation (GDPR) to protect and handle personal data, and the data were securely stored in an anonymised format, with each participant assigned a unique user ID that was arbitrarily defined.
3.2 Propensity score matching method

To accurately analyse how an intervention or program (treatment) could influence a system, it is critical to examine the performance of the same system if the intervention had not been introduced, the so-called "control group". Randomised control trial experiments are studies in which the control group is drawn randomly from the sample, and thus potential selection bias is eliminated. These methods are powerful; however, they might be less practical to implement in some types of transport studies, such as traffic safety, vehicle membership, carsharing and travel demand (Ding et al., 2021; fka Andersson et al., 2021; Zhang et al., 2021).

In this study, we aim to understand how being an e-scooter user could affect the modal shift of users. We used propensity score matching (PSM) to estimate this effect. PSM method has been frequently applied in similar transport domains such as the impact of carsharing on travel behaviour (Mishra et al., 2015), bike highway on the usage of bike hire (Li et al., 2018), to estimate the causal impact of intervention/treatment on the outcome.

The probability of treatment assignment based on observed baseline characteristics is known as the propensity score (Austin, 2011). The PSM technique uses a single index (propensity score) to build a counterfactual control group based on several matching covariates. The difference in average modal substitution \((Y)\) between e-scooter users \((SU=1)\) and e-scooter non-users \((SU=0)\) can be specified as Eq (1):

\[
\Delta = E \left[ Y_{1,i} | SU_i = 1 \right] - E \left[ Y_{0,i} | SU_i = 0 \right]
\]

\[
= E \left[ Y_{1,i} | SU_i = 1 \right] - E \left[ Y_{0,i} | SU_i = 1 \right] + E \left[ Y_{0,i} | SU_i = 1 \right] - E \left[ Y_{0,i} | SU_i = 0 \right]
\]

Eq 1 can be decomposed into two parts. The first part represents the causal effect, and the latter represents a selection bias. Let's consider \(i\) as several units of study, where \(i = 1, 2, \ldots \) and \(N\) (i.e.,
individual members). The first two terms of this equation (second line) represent the average causal effect of being an e-scooter user \((SU_i = 1)\). In other words, this shows the expected difference between the observed outcome \((Y_{1,i})\) and a counterfactual outcome \((Y_{0,i})\), if the users were not users. More specifically, the first two terms describe the average treatment effect on the treated (ATT). The last two terms show the self-selection bias as the expected difference between the counterfactual outcome of users if they were not users \((Y_{0,i}|SU_i = 1)\), and the observed outcome of non-users \((Y_{0,i}|SU_i = 0)\).

To implement the PSM, we followed three steps:

i) Prediction of the propensity score

This step is dedicated to estimating propensity scores, which could be implemented via different categories of discrete choice models. In other words, this step estimates the probability of an individual being an e-scooter user conditional on the baseline of confounding covariates. In doing so, a logistic regression model with a linear model function is adopted (Eq 2).

\[
e(X_i) = P(SU_i = 1|X_i = x^{(c)}) = P_i
\]

\[
\log \left[ \frac{P_i}{1 - P_i} \right] = \alpha + \beta x_i^{(c)} \quad i = 1, 2, ..., N
\]

where \(e(X_i)\) is the propensity score obtained by regressing \(SU_i\) on confounding factors specified by \(X_i\). Also, \(\beta\) is the vector of regression coefficients concerning the confounding factor vector \(x^{(c)}\), and \(\alpha\) is the intercept.

ii) Matching

Each unit of the treatment group should be paired with a similar one in the control group according to their propensity score value. Several matching methods, such as K-nearest neighbours matching, subclassification matching, caliper and radius matching, and kernel could be applied for matching. We used caliper and nearest neighbour matching methods and selected the nearest neighbour that
yielded the most discrepancy between the mean of the confounding factors. These matching methods have demonstrated their success in previous transport-related studies (Xiao et al., 2023; Zhang et al., 2021).

iii) Estimation of treatment effect

In the last step, the effect of treatment (being an e-scooter user) is estimated by evaluating the treatment and matched control units. This represents how being an e-scooter user could affect users' modal substitution probability.

We wrote our code in Python programming language for restructuring and cleaning data and used the Psmatch2 package in STATA to implement the PSM method (Leuven & Sianesi, 2003). To obtain valid causal inference from PSM, the model needs to satisfy three main assumptions:

i) Conditional independence assumption (CIA)

The CIA represents the state that conditional on the observed confounding factors $X_i$, the treatment assignment should be independent of the potential outcomes. This conditional dependence can also be obtained by conditioning on a scalar rather than high-dimensional baseline covariates (Rosenbaum & Rubin, 1983). Eq 3 represents CIA formulation.

\[
SU_i \perp (Y_{0,i}, Y_{1,i}) | X_i \\
= SU_i \perp (Y_{0,i}, Y_{1,i}) | e(X_i)
\] (3)

ii) Common support condition (CSC)

This assumption (also called overlap assumption) is intended to check if a control group can be detected for each treatment group. This assumption could be tested by mapping the distribution of the control group's propensity score against the treatment group's propensity score. In other words, the conditional distribution of $X_i$ when $SU_i = 1$ should overlap the conditional distribution of $X_i$ when $SU_i = 0$. Eq 4 specifies CSC:
\[ 0 < p(SU_i = 1 | X_i) < 1 \quad \text{including all } x \] 

\[(4)\]

iii) Stable unit treatment value assumption (SUTVA)

The main requirement to satisfy SUTVA is that each unit's outcome must be independent of how other units are being treated (Graham et al., 2014).

4. Results and discussion

In this section, we provide the results and discuss them within the body of literature. In this section, we briefly discuss 4.1) data; 4.2); propensity score model; 4.3) matching results; 4.4) impact of the e-scooter program on modal substitution; and 4.5) finding's implications.

4.1 Data

The data collection process took about one month, within April 2022. In total, 1806 responses were received. We considered several checkpoints to assess the quality of the data. First, we removed the participants' records who answered the survey fast (i.e., faster than 150 sec). Next, we designed questions to capture contradictory responses. For instance, if a participant positively answered about having experience with e-scooters in one question, they could not answer that they had never ridden e-scooters in another question. Moreover, we did not interpolate missing values for any questions and therefore removed the record of participants with even one missing value. After cleaning data, 805 records met the criteria to be included in data analysis. Table 2 presents the included variables from the survey. Our sample exhibits some biases in terms of participants' demographic characteristics. Specifically, as can be seen from Table 2, we have observed a higher proportion of female participants and individuals with current employment status. While this type of skew is not atypical in survey-based studies, it is crucial to recognise its potential impact on the results of the PMS analysis. It should be noted that the survey also had questions regarding parking issues and trip comfort, which are excluded from this study.
4.2 Propensity score model

To estimate the model, three variables from the survey, including having a job, the primary transport mode, and how they get to public transport were used in the logistic regression. Subsequently, we iteratively added one covariate at a time and checked the likelihood ratio test to decide if the variable should be included in the model specification. The primary purpose of the propensity score model is to build an index to reflect all confounding factors, not to predict treatment assignment. Table 3 presents the estimation results of the logistic regression model. This section briefly discusses the multivariate correlations obtained in this model. The coefficients indicate that e-scooter users are less likely to be female, old, and have teenage dependents between (13 to 17) in their household. On the other hand, e-scooter users are more likely to have jobs with high salaries and children between 7 and 12 in their household.

When it comes to vehicle holdings, we find statistically significant effects of having an e-bike and car in the household of e-scooter users. It is also likely that they use their cars frequently (more than several times per day). The connection with car usage is also reflected in the fact that e-scooter users are likely to have a driving licence. For other modes of transport, we find that they are less likely to be frequent bike users, and to walk or cycle to get to public transport. Plus, it is more likely that e-scooter users have monthly access cards for both e-scooter and public transport. The average overall trip duration of e-scooter users is shorter than 30 min.
Table 2. Summary of variables included in the survey

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Percentage of indicator</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Socio-demographic factors</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gender</td>
<td>Female indicator (1 if the respondent is a female, 0 otherwise)</td>
<td>58%</td>
</tr>
<tr>
<td>Age</td>
<td>Year  Ave: 44; Min: 16; Max: 88</td>
<td></td>
</tr>
<tr>
<td>Household structure</td>
<td>Having children between the age of 7-12 in the household (1 if the respondent answers &quot;Yes&quot;, 0 otherwise)</td>
<td>20%</td>
</tr>
<tr>
<td></td>
<td>Having teenage between the age of 13-17 in the household (1 if the respondent answers &quot;Yes&quot;, 0 otherwise)</td>
<td>18%</td>
</tr>
<tr>
<td>Job</td>
<td>Having a job (1 if the respondent answers &quot;Yes&quot;, 0 otherwise)</td>
<td>64%</td>
</tr>
<tr>
<td>Income</td>
<td>High salary job* (1 if the respondent answers &quot;Yes&quot;, 0 otherwise) *The threshold is 30,000 SEK -Swedish Kroner</td>
<td>40%</td>
</tr>
<tr>
<td><strong>Travel history/habit factors</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>E-bike owners</td>
<td>Having an e-bike in the household (1 if the respondent answers &quot;Yes&quot;, 0 otherwise)</td>
<td>21%</td>
</tr>
<tr>
<td>Personal car owners</td>
<td>Having a car in the household (1 if the respondent answers &quot;Yes&quot;, 0 otherwise)</td>
<td>63%</td>
</tr>
<tr>
<td>Work trips by bikes</td>
<td>Using a bike for work trips (1 if the respondent answers &quot;Yes&quot;, 0 otherwise)</td>
<td>29%</td>
</tr>
<tr>
<td>Work trips by cars</td>
<td>Using a car for work trips (1 if the respondent answers &quot;Yes&quot;, 0 otherwise)</td>
<td>40%</td>
</tr>
<tr>
<td>Bike as a frequent transport mode</td>
<td>Using a bike more than several times per day for all types of trip purposes (1 if the respondent answers &quot;Yes&quot;, 0 otherwise)</td>
<td>50%</td>
</tr>
<tr>
<td>Car as a frequent transport mode</td>
<td>Using a car more than several times per day for all types of trip purposes (1 if the respondent answers &quot;Yes&quot;, 0 otherwise)</td>
<td>65%</td>
</tr>
<tr>
<td>Duration of work trips</td>
<td>More than 30 min indicator (1 if the respondent answers &quot;Yes&quot;, 0 otherwise)</td>
<td>47%</td>
</tr>
<tr>
<td>Duration of leisure trips</td>
<td>More than 30 min indicator (1 if the respondent answers &quot;Yes&quot;, 0 otherwise)</td>
<td>30%</td>
</tr>
<tr>
<td>Accessing to public transport</td>
<td>Accessing to public transport by walking and/or cycling (1 if the respondent answers &quot;Yes&quot;, 0 otherwise)</td>
<td>91%</td>
</tr>
<tr>
<td>Driving licence</td>
<td>Having a driving licence (1 if the respondent answers &quot;Yes&quot;, 0 otherwise)</td>
<td>74%</td>
</tr>
<tr>
<td>Public transport monthly card</td>
<td>Having a monthly card indicator (1 if the respondent answers &quot;Yes&quot;, 0 otherwise)</td>
<td>50%</td>
</tr>
<tr>
<td>E-scooter monthly card</td>
<td>Having a monthly card indicator (1 if the respondent answers &quot;Yes&quot;, 0 otherwise)</td>
<td>13%</td>
</tr>
</tbody>
</table>
Table 3. Summary of results of propensity score model (logistic regression model)

<table>
<thead>
<tr>
<th>Confounders</th>
<th>Coef.</th>
<th>SE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>2.576***</td>
<td>0.199</td>
</tr>
<tr>
<td>Gender</td>
<td>-0.381***</td>
<td>0.075</td>
</tr>
<tr>
<td>Age</td>
<td>-0.071**</td>
<td>0.002</td>
</tr>
<tr>
<td>Children dependent (between 7 to 12)</td>
<td>0.203**</td>
<td>0.095</td>
</tr>
<tr>
<td>Teenage dependents (between13 to 17)</td>
<td>-0.608***</td>
<td>0.105</td>
</tr>
<tr>
<td>Job</td>
<td>0.488***</td>
<td>0.088</td>
</tr>
<tr>
<td>Income</td>
<td>0.609***</td>
<td>0.081</td>
</tr>
<tr>
<td>E-bike owners</td>
<td>0.769***</td>
<td>0.102</td>
</tr>
<tr>
<td>Personal car owners</td>
<td>0.280***</td>
<td>0.080</td>
</tr>
<tr>
<td>Work trips by bikes</td>
<td>0.175*</td>
<td>0.153</td>
</tr>
<tr>
<td>Work trips by cars</td>
<td>-0.405*</td>
<td>0.238</td>
</tr>
<tr>
<td>Bikes as a frequent transport</td>
<td>-0.342***</td>
<td>0.099</td>
</tr>
<tr>
<td>Car as a frequent transport</td>
<td>0.158**</td>
<td>0.084</td>
</tr>
<tr>
<td>Duration of work trips</td>
<td>-0.216***</td>
<td>0.035</td>
</tr>
<tr>
<td>Duration of leisure trips</td>
<td>-0.078**</td>
<td>0.038</td>
</tr>
<tr>
<td>Accessing to public transport</td>
<td>-0.110***</td>
<td>0.033</td>
</tr>
<tr>
<td>Driving licence</td>
<td>0.618***</td>
<td>0.094</td>
</tr>
<tr>
<td>Public transport monthly card</td>
<td>0.323***</td>
<td>0.075</td>
</tr>
<tr>
<td>E-scooter monthly card</td>
<td>0.486***</td>
<td>0.139</td>
</tr>
<tr>
<td>McFadden's pseudo R-squared</td>
<td>0.285</td>
<td></td>
</tr>
</tbody>
</table>

Note: *p <0.1; **p <0.05; ***p <0.01

4.3 Matching results

Prior to using the estimated propensity score for matching, we examine the "common support" condition. This is the second assumption of the PSM method, discussed in 3.2 Propensity score matching method. The propensity score distributions for both e-scooter users and non-users are shown in Figure 2. The histogram demonstrates the treatment and control groups overlap for all score ranges. This confirms that there is no treated unit outside the region of common support; thus, no observations must be discarded. Consequently, we infer that the overlap assumption is viable in our empirical analysis. This testing method has been frequently applied in previous studies in the transport domain (Ding et al., 2021; Li et al., 2018; Zhang et al., 2021).
Following the matching step, the PSM technique attempts to balance the distribution of confounders between the e-scooter users and non-users' groups (treatment and control groups, respectively). To further inspect the quality of matching, we performed the balance test for caliper and nearest neighbour matching methods. We exclude the result table for brevity, but the parameter estimates show improved overall balance of all confounding factors.

![Figure 2](image-url)

**Figure 2** Results of overlap test based on propensity score distribution

### 4.4 The impact of the e-scooters on modal substitution

In this section, we estimate the impact of using e-scooters on modal substitution for short distance trips (less than 4 km). In other words, we explore how being an e-scooter user could increase/decrease the probability of modal shift – the so-called effect of treatment on treated. To elicit participants' opinions regarding their modal shift, we asked respondents about the probability of shifting to e-scooters from their frequent mode (i.e., very likely, moderately likely and less
likely). We combined the positive responses (i.e., very likely and moderately likely) versus the negative ones (less likely) and built a binary response. In the binary response, 1 represents the inclination towards shifting to use an e-scooter and 0 otherwise. The results indicate that being an e-scooter user increase 46% the probability of a modal shift to e-scooters. Table 4 summarises the results of the average treatment in the treated group. The ATT row in Table 4 presents the comparison between e-scooter users and non-users (control) regarding the probability of modal shift. It demonstrates that e-scooter users have a higher probability of modal shift compared to non-users. To assess the magnitude of this difference in a relative sense, we consider the control probability in the ATT row as a reference point. By comparing the probability of modal shift between e-scooter users and non-users relative to this reference point, we can determine the percentage increase.

Table 4. Results of the PSM model for the impact of the e-scooter program on modal shift

<table>
<thead>
<tr>
<th>Variable</th>
<th>sample</th>
<th>Treatment</th>
<th>Control</th>
<th>Difference</th>
<th>SE</th>
<th>T-stat</th>
<th>Effects (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Modal shift</td>
<td>Unmatched</td>
<td>0.5934</td>
<td>0.2192</td>
<td>0.3742</td>
<td>0.013</td>
<td>28.66</td>
<td></td>
</tr>
<tr>
<td></td>
<td>ATT</td>
<td>0.5934</td>
<td>0.4065</td>
<td>0.1868</td>
<td>0.065</td>
<td>2.85</td>
<td>*46%</td>
</tr>
</tbody>
</table>

Note: *Statistical significance at the 5% level.

This result shows that e-scooters can impact the modal shift of users for trips under 4 km. It should be noted that this result does not directly reflect which transport modes will be directly replaced by e-scooters. Our results show that they are frequent car users, indicating that some of these trips may be replaced, but also that they are holders of monthly public transport cards, which could imply that public transport trips are replaced instead.
4.5 Finding's implications

In this section, we discuss the application of the study and map them against the existing literature. This section contains i) e-scooter users' characteristics, ii) the impact of using e-scooter in modal substitution, and iii) limitations and outlook.

i) E-scooter users' characteristics

In terms of e-scooter users' socio-demographic characteristics, they are less likely to be women and older. This finding is in line with the literature, as e-scooter riders are reported to be more likely male and young adults (Kazemzadeh & Sprei, 2022). Also, e-scooter users are more likely to have a job with a high salary which is in agreement with previous research findings (Yang, Bao, et al., 2022). It is worth noting that several previous studies reported such findings based on university towns, while the current study obtained similar results based on case studies in two large Swedish cities. Therefore, being male-dominant, users with a job and high salary could be expected to describe the socio-demographic characteristics of e-scooter users regardless of the size of the city. We also found that e-scooter users are less likely to have a dependent teenager in their household than younger children. This finding is an addition to the literature as it describes the household structure of users. Having children in the household might reinforce the need for the trips of two persons simultaneously (e.g., picking up children from school). In sum, our results give a more nuanced and richer picture of e-scooter users' socio-demographic characteristics.

Our results on the vehicle ownership and general transport behaviour, i.e., that they are likely to own both cars and e-bikes, as well as holding monthly public transport and e-scooter access cards, is an addition to the literature by showing that e-scooter users could be considered highly mobile people and interested in the multimodal transport system. Also, e-scooter users are more likely to use bikes for commute trips and less likely to have work trips longer than 30 min. Hence, our
results give a mixed picture when it comes to other modes of transport. E-scooter users frequently use the car, but more likely to own an e-bike and have a monthly public transport card. This is an indication that being an e-scooter user can be correlated with higher mobility and maybe even multimodal.

Juxtaposing the characteristics of e-scooter users with other transport modes can provide valuable insights for policymakers and planners. First, the user of shared mobility is deemed to be a young adult, as in the case of carsharing (Becker et al., 2017; Dias et al., 2017). Second, comparing the age range of electrically assisted transport modes shows that e-bikes enable older adults to use active modes while e-scooter users are mainly younger adults (Kazemzadeh & Ronchi, 2022). This might be due to the longer history of e-bikes compared to e-scooters, the similarity of e-bikes to conventional bikes, and thus their acceptance as a transport mode among older adults. Also, the riding postures of these modes are different, and e-scooter riders need to stand up, which is not the case for e-bikers, which might be a barrier for older adults. Finally, male users are overrepresented in both bike and e-scooter modes which could affect transport and gender equity (Burghard & Dütschke, 2019; Cao et al., 2021). This essential factor needs further assessment in future research, and its causes should be evaluated.

ii) The impact of using e-scooter in modal substitution

E-scooters are easily accessible, faster than conventional cycling and walking and more enjoyable to use due to the electrically assisted riding experience (Foissaud et al., 2022; Kazemzadeh & Bansal, 2021a). They can substitute and supplement existing modes, which can have an impact on the supply and demand system. Therefore, studying their impact and role in modal substitution and supplement is important to manage the supply and demand of the transport system effectively, and to provide sustainable, efficient, and safe modes of transport to the public.
To address this research need, we took two steps in this study. First, we explored the confounders to present who are e-scooter users, which is summarised in the previous section. This step is crucial as it can show how the characteristics of emerging mode users, in this case, e-scooter, differ from or are similar to other modes and thus discuss potential trip shifts. Second, based on the characteristics that described an e-scooter user, we quantified how being an e-scooter user could affect the probability of modal shift – the so-call impact of treatment on the treated. We found being an e-scooter user will positively increase the probability of shifting the frequent mode of users to an e-scooter for shorter trips. This result shows that the e-scooter program strongly impacts the modal shift decision of users toward e-scooters. It should be noted that we could not directly reason for which mode will primary will be replaced by e-scooters. Given that e-scooter users are likely to have frequent car trips, it is probable that some of these trips will be replaced by e-scooters. However, e-scooter riders are also likely to have a monthly public transport card.

Previous studies claimed mixed results for transport modes that e-scooters could replace (see 2.2 The impact of e-scooters in the modal shift for more details). Indeed, the favourable scenario is that e-scooter substitute motorised vehicles and contribute to a more environmentally friendly society. However, supplementing conventional cycling and walking with e-scooters could also be beneficial for users as e-scooter might increase trip comfort by a faster and still active transport mode. Yet, more research is needed to evaluate how the substitution of other transport modes by e-scooter could affect the environment considering the life cycle assessment of e-scooters. This body of literature is required to guide planners and policymakers to have realistic expectations of such emerging modes' impact on the environment.
iii) Limitations and outlook

This research inevitably has some (de)limitations. First, we only considered the resident of the two Swedish cities (i.e., Stockholm and Gothenburg). This study is representative of a similar Nordic context; however, this might impact the generalisability and transferability of the findings in other countries. Moreover, it is essential to acknowledge that our sample exhibits some biases in terms of participants' demographic characteristics. Specifically, we have observed a higher proportion of female participants and individuals with current employment status. Since e-scooter usage is more common among men this could imply, e.g. that we slightly underestimate the substitution effect. Second, the survey was written in Swedish; thus, English-speaking participants were excluded. Third, we only considered participants 16 years or older who legally can rent and use e-scooters. However, the younger adult might use e-scooters, and their perspectives are excluded from this study. Fourth, a large percentage of dummy variables could restrict the benefits of a flexible spline definition of the link function.

Future research could expand the scope of this study by comparing e-scooter users in Swedish cities with those in other Nordic countries and worldwide, providing a comprehensive analysis of user characteristics. Additionally, examining the simultaneous impact of multiple shared modes of transport, such as e-bikes, on users' modal shift decisions could aid in managing travel supply and demand. To broaden the demographic representation, future studies could also consider the perspectives of younger children who may use e-scooters despite being under the age of 16. Furthermore, exploring the impact of safety concerns on e-scooter usage, which was not included in the current analysis, could shed light on essential factors influencing adoption.
5. Conclusion

This study provides a novel framework to understand the impact of e-scooter programs on modal substitution. We surveyed 805 Swedes to investigate the socio-demographics, travel history, and habits of e-scooter users and then estimate how being an e-scooter user may impact the probability of modal shift. Through PSM, we can get more robust results that take into consideration of non-users, which is not often used in the literature on e-scooters, where normally only users are surveyed. Our results give a more nuanced picture of e-scooter users. Similar to the literature we find that being a younger man increases the probability of being an e-scooter user. However, we also find that they have a higher salary and are more likely to have kids aged 7-12 in the household.

When it comes to other transport modes, we find that they are likely to have a car and e-bike and having a monthly public transport card. Trip length wise they are more prone to have shorter trips. Thus, we can presume that e-scooter users are highly mobile people and that they are open to different transport modes. Furthermore, being an e-scooter user increases the probability of users shifting to an e-scooter by 46% for short distance trips. The findings have applications for policymakers to understand the target demographic for e-scooter usage better, know the impact of using e-scooter on modal shift, and tailor their policies and regulations accordingly.
References


Leuven, E., & Sianesi, B. (2003). PSMATCH2: Stata module to perform full Mahalanobis and propensity score matching, common support graphing, and covariate imbalance testing.


