How does parking regulation policy affect e-scooter sharing systems: A data-driven approach and analysis in Nordic cities

Transport Policy 187 (2026) 104301

Contents lists available at ScienceDirect

Transport Policy

journal homepage: www.elsevier.com/locate/tranpol

How does parking regulation policy affect e-scooter sharing systems: A data-driven approach and analysis in Nordic cities

Zhe Zhang [a], Ruo Jia [b], Yuan Liao [c,d], Marina Wiemers [e], Ying Yang [f], Zhong-Ren Peng [g,h], Kun Gao [b,*]

[a] School of Vehicle and Mobility, Tsinghua University, Beijing, 100084, China
[b] Department of Architecture and Civil Engineering, Chalmers University of Technology, Gothenburg, Sweden
[c] Department of Space, Earth and Environment, Chalmers University of Technology, Gothenburg, Sweden
[d] Department of Applied Mathematics and Computer Science, Technical University of Denmark, Lyngby, Denmark
[e] Department of Civil and Architectural Engineering, KTH Royal Institute of Technology, Stockholm, 10044, Sweden
[f] School of Management, Shanghai University, Shanghai, China
[g] International Center for Adaptation Planning and Design, College of Design, Construction and Planning, University of Florida, PO Box 115706, Gainesville, FL, 32611-5706, USA
[h] Healthy Building Research Center, Ajman University, Ajman, United Arab Emirates

ARTICLE INFO

Keywords:
E-scooter sharing
Policy
Regression discontinuity design
Usage patterns

ABSTRACT

The expansion of e-scooters sharing service presents challenges for traffic management. In response to the disruptive effects caused by e-scooters sharing, many states and cities have enacted laws, regulations, or policies to govern their operation. This study proposes a novel analytical framework, integrating regression discontinuity design and difference of probability, for systematically quantifies and comparatively analyzes the impacts of e-scooter sharing policies on usage patterns and system-level benefits. We use three cities in Sweden as representative cases to examine the implementation of e-scooter sharing policies before and after their enactment. Results indicate that Swedish policies in these cities have led to a decrease in shared e-scooter demand, especially near city centers, along with an increase in travel speeds and reduced trip duration and distance. Additionally, the policy promotes individual trips by increasing the likelihood of shared e-scooters replacing other transport modes, resulting in higher efficiency. While the policy increases the likelihood of trips that produce higher emissions, it also contributes positively to greenhouse gas emissions reduction per trip, indicating improved environmental benefits within specific urban contexts. These results provide valuable insights into the role of policy in optimizing shared e-scooter integration within urban transportation systems, ultimately contributing to more sustainable and efficient mobility solutions for cities.

1. Introduction

In recent years, shared micromobility systems, such as shared bicycles, scooters, and mopeds, have gained significant popularity worldwide (Almaskati et al., 2024). Shared micromobility, of which vehicles typically weigh less than 350 kg and operate at low speeds (typically below 45 kph), have emerged as flexible and new players in urban mobility systems (Abduljabbar et al., 2021; Emami and Ramezani, 2024) to provide users with affordable, convenient, efficient, and easily accessible transport options for short trips (Fuady et al., 2024; Yao et al., 2025; Zakhem and Smith-Colin, 2024; Zhang et al., 2021). Following the launching of the first e-scooter system by Lime in 2017, shared e-scooter system (SES) rapidly became a trend and gained a significant share of urban shared micromobility. In 2019, the number of scooter trips surged to 88.5 million, marking a staggering 130% increase compared to 2018 in the United States (NACTO, 2020). In the same year, shared e-scooter services experienced global expansion with the introduction of new systems in Europe, Asia, and Australia (Nikiforiadis et al., 2023). Shared e-scooter services were available in more than 220 cities in the United States and Europe (Mobility Foresights, 2021). In Europe alone, there are 20 million users of e-scooter sharing, with the adoption rate being four times faster than that of bike sharing (Latinopoulos et al., 2021).

Despite the acknowledged benefits of SES, the expansion and proliferation of shared e-scooters bring forth a spectrum of challenges. In

* Corresponding author.
E-mail address: gkun@chalmers.se (K. Gao).

https://doi.org/10.1016/j.tranpol.2026.104301
Received 27 December 2025; Received in revised form 12 July 2026; Accepted 14 July 2026
Available online 15 July 2026

the absence of efficient regulations and management regarding the use and parking of shared e-scooters, many cities struggled with issues such as sidewalk blocking, illegal parking, safety hazards, and legal issues (Gössling, 2020; Janssen et al., 2020). Challenges arise in managing the movement and parking of shared e-scooters on the streets, intersections, and sidewalks. For example, improper parking, such as leaving e-scooters in the middle of sidewalks, can obstruct pedestrians and increase the risk of accidents (Turoń and Czech, 2020). Consequently, about half of the reported e-scooter–related incidents have resulted in severe injuries, and fatalities have even occurred in the USA (Schlaff et al., 2019; Trivedi et al., 2019; Vernon et al., 2020; Yang et al., 2020).

In response to disturbing effects due to shared e-scooters, many states and cities have formulated laws, regulations and policies to govern the operation of shared e-scooters. Since the first appear of shared e-scooter fleet program, a majority of U.S. states introduced restrictions to control negative impacts. These restrictions include speed limits, bans of shared e-scooters on sidewalks, designated operating hours and driver's requirements (Scooters, 2019). Legislative and policy efforts have also begun to unfold in European countries, such as France, Germany and Austria, sanctioning the use of compliant e-scooters on public streets (Latinopoulos et al., 2021). The city government of Paris even announced a complete ban on the use of for-hire e-scooters, effective as of April 2023 (Zakhem and Smith-Colin, 2024). Additionally, the adaptions from existing bike sharing regulations have also been set to regulate e-scooter sharing in some European countries including Bulgaria, Belgium, Portugal, Finland, Norway and Sweden (Sokolowski, 2020). These implemented policies vary across cities in terms of speed limits, service area where it can be ridden and parked, and driving license.

Even though a lot of discussions have been made during formulating the implemented regulations and policies regarding shared e-scooters, it is still unclear how these implemented policies and regulations affect the system performances of shared e-scooters. Particularly, solid evidence and quantitative assessment based on big data regarding the effects of implemented policies and regulations are lacking in the state-of-the-art research. Understanding the actual and quantitative effects of different policies and regulations on the shared micromobility systems is crucial for the policy makers and planners to post-evaluate the effectiveness of implemented policies and to develop and formulate more effective and tailored future policies, which plays an important role in sustainable management and development of shared micromobility systems.

In order to address the research gaps outlined above, this study proposes a novel analytical framework for systematically quantifying the impacts of e-scooter sharing policies on usage patterns and system-level benefits using real-world before-and-after field data. The proposed framework integrates several approaches, including regression discontinuity design (RDD) and Difference of Proportions (DoP) analysis and model-based analysis, to quantify the policy effects on shared e-scooter usage patterns, time savings, and greenhouse gas emission reductions. Unlike the studies that rely primarily on simulation or aggregate statistics, this framework leverages realistic trip transaction data of shared e-scooters from three Swedish cities before and after an implemented policy, thereby capturing the impacts of policy interventions in diverse urban contexts. Furthermore, the RDD component effectively controls for confounding endogenous factors and external noise, ensuring that the identified policy effects are both statistically valid and causally interpretable. Based on this framework, an empirical city-level analysis is conducted to captures changes in shared e-scooter usage, operational efficiency, and environmental performance between the pre- and post-policy periods. By combining causal evidence, descriptive comparisons, and model-based estimation, the framework systematically quantifies the shared e-scooter policy effects, offering a robust, multi-dimensional assessment of system benefits. The findings contribute not only a methodological advancement for evaluating shared mobility policies but also provide valuable insights for policymakers and urban planners seeking to optimize urban mobility systems in a sustainable and efficient manner.

The remaining sections are structured as follows. Section 2 reviews existing literature to highlight research gaps. Section 3 elaborates on the data and details of used analysis methods, followed by results and discussions in section 4. The concluding remarks and further research directions are summarized in Section 5.

2. Literature review

Since the emergence and popularity of shared e-scooters, the research community has demonstrated much interest in it. Existing research primarily concentrates on several areas, including usage patterns (Badia and Jenelius, 2023; Huo et al., 2021; Mehzabin Tuli et al., 2021), effects on other transportation modes (Gu et al., 2024; Guo and Zhang, 2021; Kazemzadeh and Sprei, 2024; Kim et al., 2023; Mitropoulos et al., 2023), and safety hazards (Janikian et al., 2024; Kazemzadeh et al., 2023; Ma et al., 2021b; Sexton et al., 2023).

However, a comprehensive understanding of the challenges encountered by shared e-scooters and the influence of policies and regulations on their system performances remains underexplored. There are debates regarding the authorization of shared e-scooters due to significant uncertainty and disruption caused by them (CNN, 2018). Gössling (2020) alerted that city planners should be mindful of power struggles, forms of social and cultural resistance, as well as infrastructural and technical barriers. They explored the challenges linked with the introduction of shared e-scooters in ten major cities through a content analysis of local media reports. The findings suggested that policies concerning maximum speeds, compulsory utilization of bicycle infrastructure, dedicated parking, and limiting the number of licensed operators should be judiciously implemented. Tailored policies have been emphasized by media (The Guardian, 2019) and researchers (Abouelela et al., 2023; Oluwajana and Wang, 2023) to regulate shared e-scooters.

Several studies have examined the benefits or negative impacts of policies and regulations (such as laws, regulations, guidelines or rules) on shared e-scooters. One study provided an overview of policies in 156 U.S. cities (Ma et al., 2021a). The results showed a clustered pattern in space regarding policies of shared e-scooters including where to park, where to ride, helmet requirements, sidewalk restrictions, and how to report issues. Subsequently, best practice for municipal policy on shared e-scooters in the U.S. was also explored with the goal of identifying policy patterns (Riggs et al., 2021). The effectiveness of current safety regulation in Austin was discussed to measure whether it addressed the risk factors (Salas-Niño, 2022). Additionally, the impacts of city regulations on modal choices have been studied (Roig-Costa et al., 2024). The finding revealed that these policies might determine individual's choice between different modes of micromobility. There are also some studies focusing on optimizing operations of shared e-scooters within the framework of existing policies. For instance, Zakhem and Smith-Colin (2024) devised a guidance tool to allocate routes to shared e-scooters while considering city rules and regulations. This tool, proposed for integration into provider applications, aimed to enhance rider safety, comfort, and compliance by directing users to appropriate routes and parking locations. The viability and economics of shared e-scooters within the context of the regulatory environment were also be reviewed by (Button et al., 2020). Meanwhile, some researchers have explored the effectiveness of different regulatory strategies in managing Micromobility Sharing Systems (MSS) across several European cities, analyzing both their advantages and drawbacks (Bach et al., 2023). Additionally, investigations into the effects of the stay-at-home policy on Citi Bike usage in Manhattan during the COVID-19 pandemic have been conducted (Lei and Ozbay, 2021). Furthermore, studies quantifying the influence of congestion pricing on ride-hailing ridership in Chicago can offer insights into the impact of policies on shared e-scooters (Zheng et al., 2023).

Yet, most studies of analyzing the effects of policy and regulation on

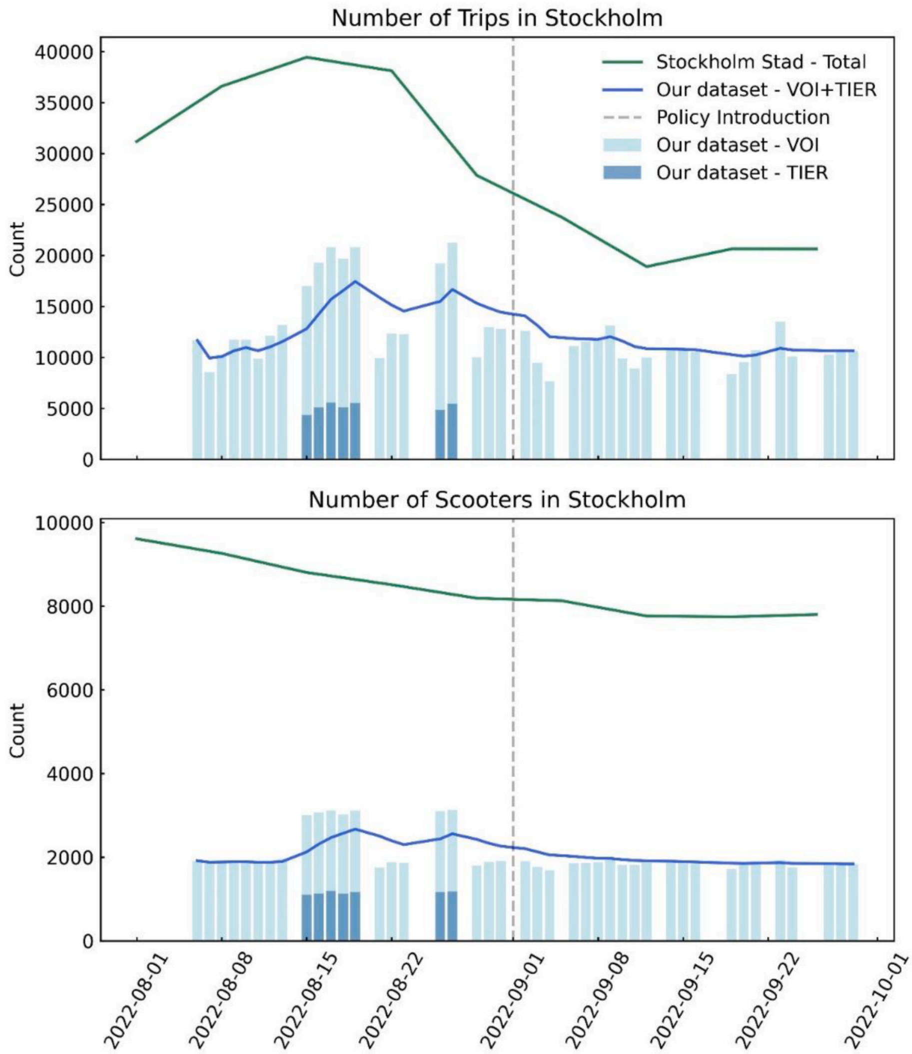

Fig. 1. The number of trips and vehicles in official data and our dataset.

shared e-scooters have relied on survey methods, which are straightforward and easy to conduct. However, the inherent limitations of surveys are unreliable sample biases due to small sample sizes and infeasibility to conduct high-resolution investigations for the effects of policy and regulations on different areas of a city. These limit quantitative understanding and insights into the actual effects of different policies and regulations on shared e-scooter systems, to support future effective policy and regulation decision making. The potential of leveraging emerging big data resources to conduct data-driven comparative and high-resolution analyses of policy impacts before and after implementation based on field data remains largely untapped. The difficulty of conducting big-data-driven investigation lies in several aspects: 1) the difficulty of collecting qualified and comparable data exactly before and after policy implementation for the same study area that cover different city contexts with different socio-economic and built environment; 2) the difficulty of effective methodology to get the pure effects of implemented policy on system performances of shared e-scooters, omitting the exogeneous effects of other relevant factors (e.g., weather and fleet size). Being aware of the research gap, this study aims to utilize historical big data from shared e-scooter systems before and after a policy implementation to investigate how the policy intervention affected different aspects of shared e-scooters. Crucially, we seek to provide empirical evidence of the effectiveness of policy interventions in shaping usage patterns and system performances based on field big data in different urban contexts, which cannot be obtained from survey data. This comparative analysis will shed light on the potential impacts of regulatory measures on system performances of shared e-scooters, and thus offer valuable insights for policymakers, urban planners, and stakeholders to better management of the system in different urban contexts.

3. Study area and datasets

3.1. Study area

Sweden has been promoting shared e-scooters. However, urban planners, service providers, and municipal governments are grappling with challenges of shared e-scooters for promoting it as part of sustainable urban mobility. The Swedish government introduced a new regulation at the beginning of September 2022 to regulate the operation and use of share e-scooters, aiming to establish clearer guidelines and ensure safer practices. The regulation implemented on September 1, 2022, represents a prominent example. This policy includes two main aspects: (1) Shared e-scooters cannot be parked on footpaths and cycling paths. Parking is only permitted in cycle racks or designated places. (2) shared e-scooters may no longer be ridden on footpaths. Therefore, this study takes this policy as the research focus to investigate the quantified policy effects of e-scooter policy. To evaluate the regulatory effects on usage patterns and system performances of shared e-scooters, this study focuses on three largest cities in Sweden including Stockholm,

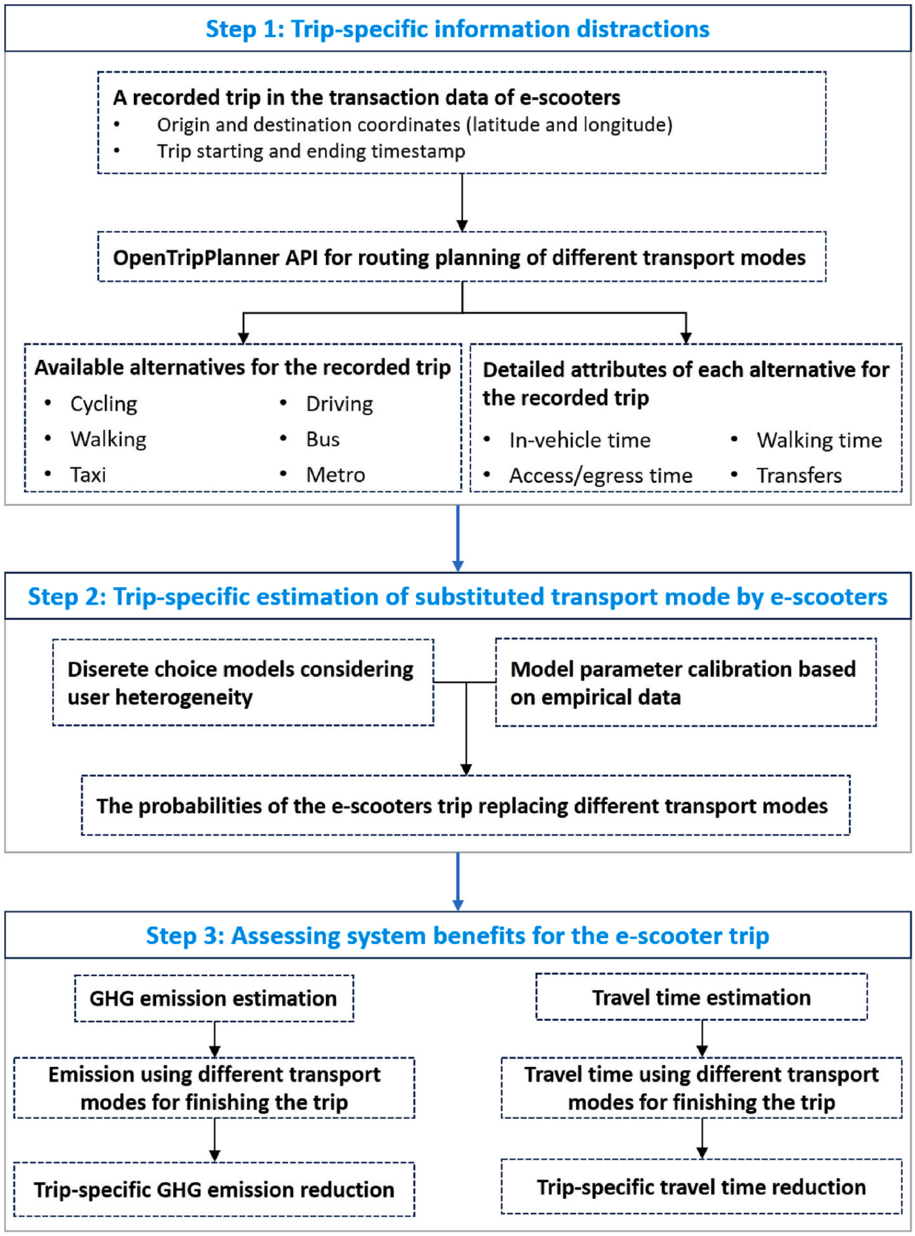

Fig. 2. The framework of system benefits estimation (Gao et al., 2024).

Gothenburg, and Malmö. As of 2022, Stockholm had a population of approximately 1.679 million in its metropolitan area, Gothenburg had about 579,281 residents, and Malmö had a municipal population of approximately 357,377 (Statistikmyndigheten SCB, 2024). The data in the three largest Swedish cities with large populations provide representative cases for analyzing changes in usage patterns and system performances before and after the implementation of the new regulations. Hereafter, Stockholm, Gothenburg, and Malmö are shortened as STH, GBG, and MLM in the following contents, respectively.

3.2. Data sources

The dataset for this study comprises shared e-scooter trips from August 1, 2022, to September 30, 2022, sourced through an open Application Programming Interface (API) from main shared e-scooter operators in Sweden. This study period is carefully selected to ensure stable environmental conditions throughout the observation window. This timeframe helps to minimize variation in external factors such as temperature and raining, which are known to have a considerable impact on shared e-scooter usage patterns. To further control for the influence of weather, all days with recorded precipitation were excluded from the dataset. These measures were implemented to ensure that the usage data reflects behavioral patterns under consistent and comparable environmental conditions. The processed data includes 519,337 trips in Stockholm, 66,173 in Gothenburg, and 124,084 in Malmö. Each trip record logs the longitude, latitude, and timestamps of starting and ending points of each trip. In Stockholm, the data mainly comes from TIER and VOI, while in Gothenburg and Malmö, it exclusively comes from VOI. TIER and Voi are both micromobility companies providing shared e-scooter services. Fig. 1 compares this dataset with official statistics from Stockholm City (Miljöbarometern, 2022) on the number of shared e-scooter vehicles and trips, illustrating a strong correlation with actual usage patterns and confirming the representativeness of our dataset. Before conducting the formal analysis, we preprocess the data to filter out anomalies. We retain trips where the distance ranges from 50 m to 20 km, the duration falls between 30 s and 1 h, and the speed is

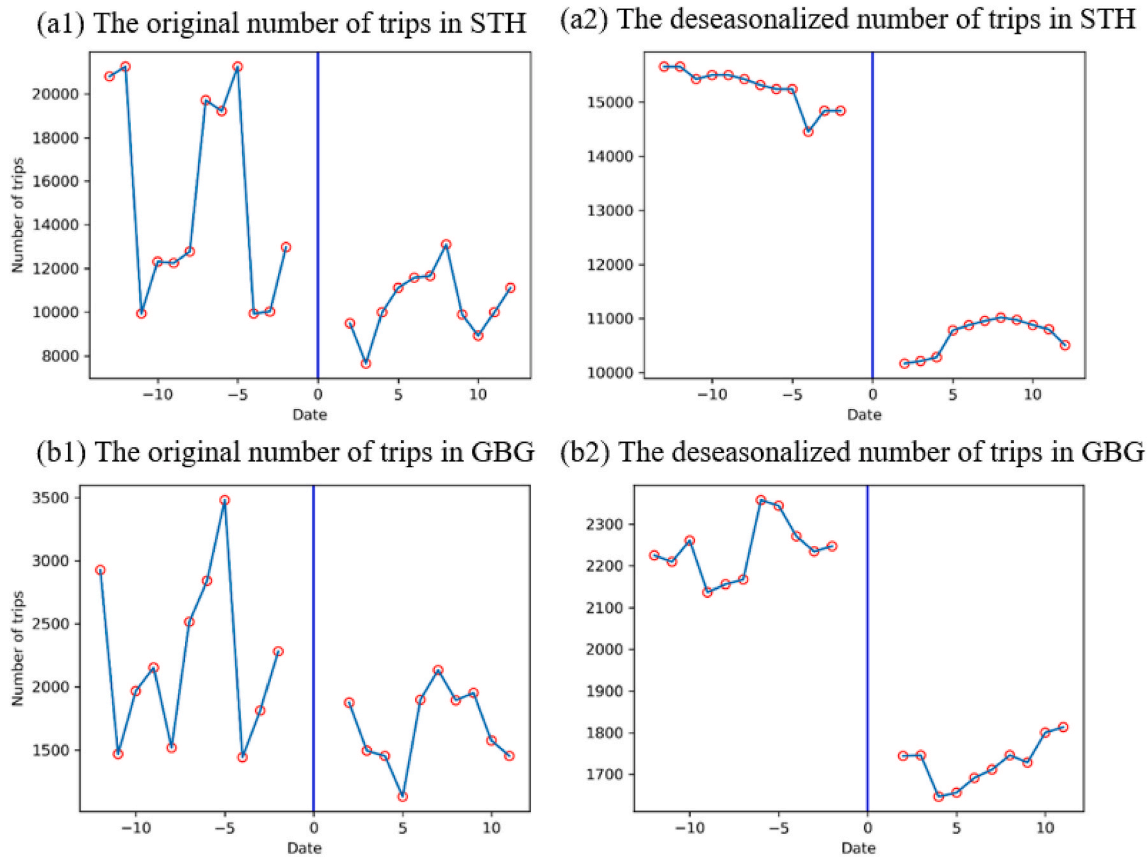

Fig. 3. Original and deseasonalized data for conducting RDD.

Table 1
RDD results for STH and GBG.

	Bandwidth	Cities	P-values	Treatment effects	Standard errors	Confidence Intervals [0.025,0.975]
Policy cutoff (September 1, 2022)	7 days	STH	0.031**	−4837.490	1803.192	[-9101.362, −573.619]
		GBG	0.001***	−610.517	110.750	[-872.399, −348.636]
	14 days	STH	0.029**	−3230.385	1377.547	[-6095.151, −365.619]
		GBG	0.000***	−535.497	58.813	[-657.805, −413.191]
	25 days	STH	0.000***	−4684.554	1065.981	[-6831.552, −2537.558]
		GBG	0.000***	−545.731	45.289	[-637.128, −454.334]
Placebo cutoff (August 19, 2022)	12 days	STH	0.147	−2539.520	1676.988	[-6062.742, 983.701]
		GBG	0.266	−91.870	80.047	[-260.043, 76.302]

***, **, and * represent statistical significance at levels of 1%, 5% and 10%, respectively.

between 2 km/h and 25 km/h considering the speed limit of shared e-scooters in Sweden during the period. This selection criteria ensures the inclusion of representative and reliable data for the analysis.

4. Methodology

This study adopts a two-part framework. RDD and DoP are complementary methods used for modeling the significance or magnitude of the changed distribution due to the regulation. First, Regression discontinuity design RDD is used to identify whether a policy-induced discontinuity exists at the implementation cutoff and provides the core causal evidence for demand effects. Second, descriptive distributional analysis is conducted for two metric groups, usage patterns and system benefits, using t-tests, Kolmogorov–Smirnov tests (K-S test), and Difference of Probability analysis. The *t*-test and K-S test assess whether the observed differences in mean values and distributions are statistically significant, while the DoP method extends beyond global metrics to quantify the magnitude and interval-specific direction of distributional changes. In other words, RDD answers whether a policy effect exists, while DoP explains how that effect is distributed. Both are required to provide a complete evaluation of policy effects in terms of both effect identification and distributional characterization.

4.1. Comparative research design

Generally, the policy effects in various areas can be analyzed through comparative research, which examines the differences before and after policy implementation to assess policy effects. In this study, shared e-scooter trips are divided into two periods: the "Pre-Policy" period, from August 1, 2022, to August 31, 2022, provides a baseline scenario before the shared e-scooter policy was implemented. The "Post-Policy" period, from September 1, 2022, to September 30, 2022, allows for the analysis of changes following the introduction of these policy measures. This division facilitates a structured comparison of shared e-scooter usage patterns before and after the policy implementation, highlighting the effects of policy on shared e-scooter systems.

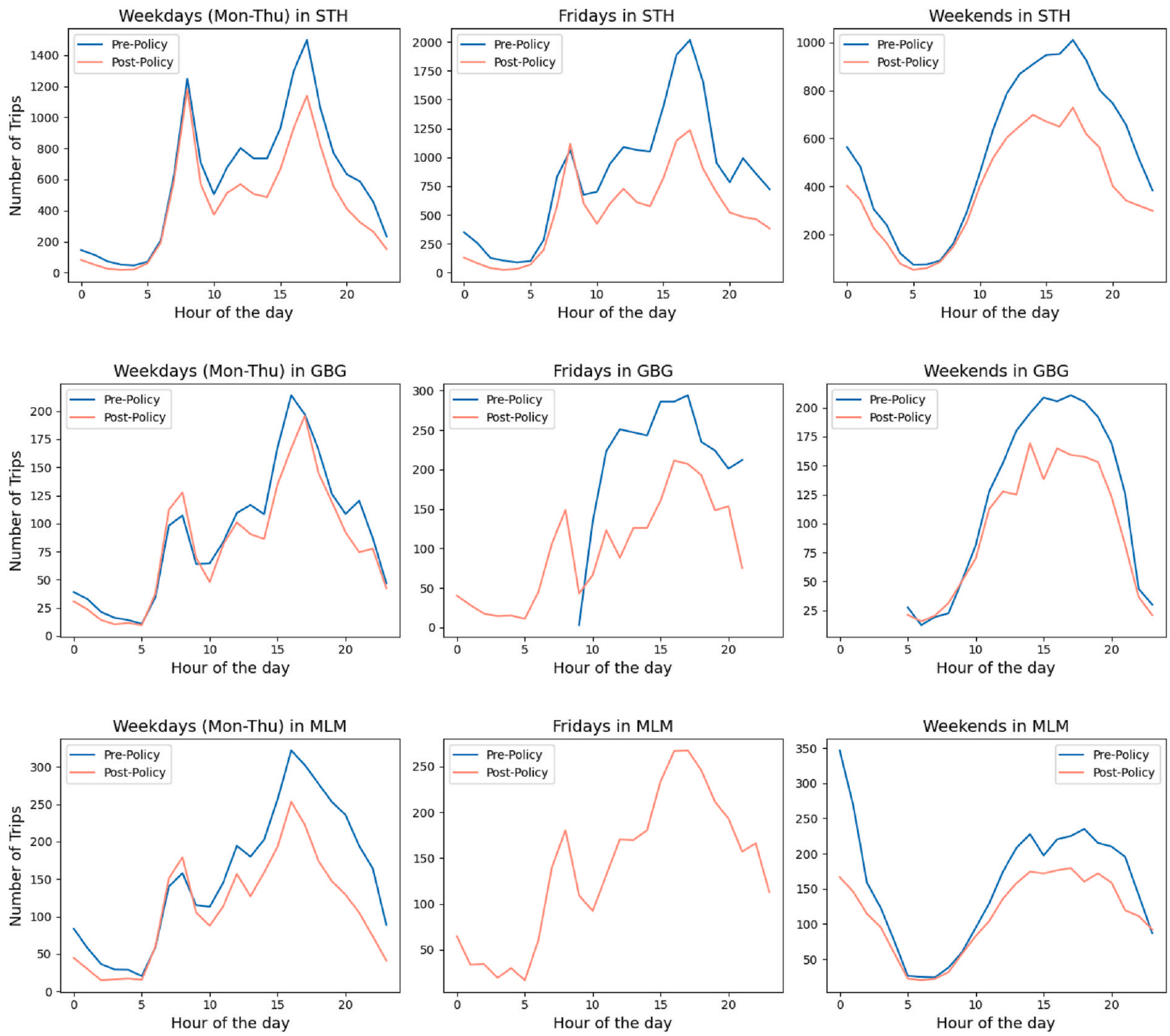

Fig. 4. The number of the trips in different days.

4.2. Causal analysis using RDD

RDD is a quasi-experimental design widely used in policy evaluation and economics to estimate causal effects. RDD is divided into two main types: Sharp RD and Fuzzy RD. Sharp RD features a clear, predetermined cutoff point that dictates policy implementation. Data points are divided into two groups based on whether they fall above or below this cutoff, ensuring a strict classification. This method focuses on the discontinuity at the cutoff, often observed as a distinct 'jump' between the two sides. When significant policy effects are present, this sharp discontinuity allows researchers to attribute observed differences in outcomes directly to the policy intervention, rather than other factors. In contrast, Fuzzy RD involves a less strict distribution around the cutoff point. Data points are not strictly divided, and the likelihood of treatment can vary continuously around the cutoff. This approach requires different analytical techniques to account for the probabilistic nature of treatment assignment. This study employs Sharp RD due to its distinct and predetermined cutoff point, which clearly separates groups before and after policy implementation. The sharp discontinuity observed at this cutoff enables us to attribute any differences in responses directly to the policy intervention, minimizing the influence of other factors.

The main regression adopted in this RDD is determined as

$$Y = \alpha_0 + \beta P + \gamma T + \sum_i \eta_i W_i^{n_i}. \tag{1}$$

Y represents the daily indicators examined for each city, capturing the shared e-scooter demand. P represents the indicator variable of the e-scooter sharing policy, which equals 1 after policy implementation and 0 before policy implementation. T is the time variable, denoting the transformation of the normalized day. Specifically, T equals 1 on the first day of the policy implementation and -1 on the last day before. T ranges from -30 to 30, covering August 1 to September 30, 2022. W denotes control variables that potentially affects Y, such as weather, economic factors and built environment. Given the stability of these factors in the short term, we focus on weather effects, including temperature and daily precipitation. Considering the non-linear nature of shared e-scooter demand, we employ polynomial fitting with weather data. $W_i^{n_i}$ is the n_i th power of the weather factor W_i. n_i is determined based on Akaike Information Criterion (AIC criterion).

Transportation-related data typically exhibit strong periodicity, particularly in demand-related aspects such as the number of trips and the number of shared e-scooters, which are needed to be examined in this study. To mitigate the deviation caused by periodic fluctuations and ensure robust findings, we performed de-seasonalization on the raw time series data before conducting the analysis. Seasonal decomposition involves breaking down a time series into three components: trend, seasonal, and residual. The trend component captures the long-term progression of the series, such as an increasing or decreasing trend over time. The seasonal component identifies repeating short-term cy-

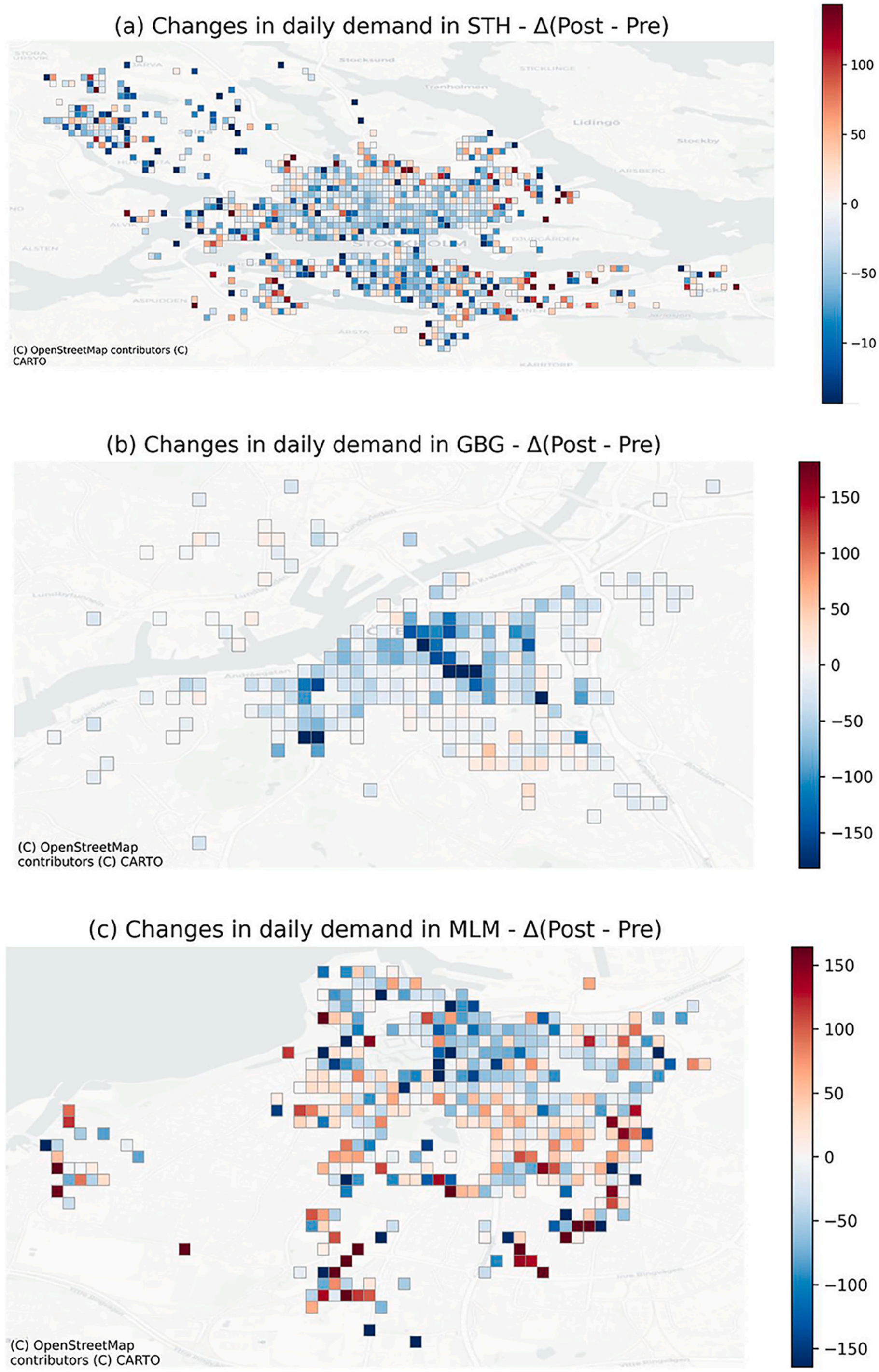

Fig. 5. Spatial changes in daily demand.

cles, such as weekly patterns in daily shared e-scooter demand. The residual component represents the remaining random noise after removing the trend and seasonal components. In this study, these three components are identified using a multiplicative model, where the indicator Y at t time step Y_t is assumed to be the product of the trend T_t , seasonal S_t and residual R_t components:

$$Y_t = T_t \times S_t \times R_t \,. \tag{2}$$

The length of the seasonal cycle is 7, which indicates a typical week. The de-seasonalized time series regarding number of trips and shared e-scooters are employed in RDD.

4.3. Descriptive comparisons using DoP

DoP proposed in this study aims to quantify the effects of the implemented policy on usage patterns and system benefits. This method is derived from the concepts of resilience (Hong et al., 2021) and vulnerability (Zhang et al., 2022). Vulnerability refers to the degree to which a system, community, or individual is susceptible to and unable to cope with adverse effects. Resilience is the ability of a system, community, or individual to withstand, adapt to, and recover from shocks or stresses while maintaining or quickly returning to its essential functions. These concepts are frequently used to analyze changes in system performance in response to disasters such as earthquakes, hurricanes, and

Table 2
t-test and K-S test results for trip characteristics.

		P value (*t*-test)	P value (KS test)	Mean (Pre-Policy)	Mean (Post-Policy)
STH	Duration (min)	0.000***	0.000***	9.731	9.046
	Distance (km)	0.000***	0.000***	1.427	1.394
	Speed(km/h)	0.000***	0.000***	9.015	9.361
GBG	Duration (min)	0.000***	0.000***	10.160	8.974
	Distance (km)	0.000***	0.000***	1.522	1.415
	Speed(km/h)	0.000***	0.000***	9.715	10.072
MLM	Duration (min)	0.000***	0.000***	9.287	8.828
	Distance (km)	0.000***	0.000***	1.443	1.431
	Speed(km/h)	0.000***	0.000***	9.807	10.159

***, **, and * represent statistical significance at levels of 1%, 5% and 10%, respectively.

even traffic jams. A common quantification method is to estimate the area under or over the curve, where the shadowed area between two curves obtained from different periods represents changes in performance. In this study, we define the shadowed area between curves before and after policy implementation as the difference attributable to the implemented policy. Specifically, we observe the shadowed area between curves of probability density to compare the differences in probability before and after policy implementation, as determined by

$$DoP = \int_{x_{\min}}^{x_{\max}} \left[A_{post}(x) - A_{pre}(x)\right] d_x. \tag{3}$$

$A_{pre}(x)$ and $A_{post}(x)$ represent curves before and after the implement of policy, respectively. $x_{\min}$ and $x_{\max}$ demotes the minimum and maximum values of specific metrics such as speed, distance and duration for a trip. To reflect the effect of the implemented policy, the DoP analysis examines the actual values of the indicators rather than the values after removing seasonality.

4.4. Metrics definition

4.4.1. Usage patterns used for descriptive analysis

To elucidate the effects of implemented policy on usage patterns, this study employs a comprehensive suite of metrics designed to capture shared e-scooter utilization from various perspectives. The focal areas of analysis include demand, trip characteristics, and usage efficiency.

Demand offers a macroscopic perspective, furnishing insights into systemic changes in travel patterns. It is quantified through metrics such as the total number of shared e-scooter trips and the count of shared e-scooters deployed. Trip characteristics provide granular details on individual travels, facilitating an examination of alterations at the trip level. This category includes indicators such as trip distance, duration, and average speed, each reflecting distinct aspects of travel dynamics. Moreover, this study investigates the usage efficiency of shared e-scooters, which may yield insights pertinent to evaluating and enhancing the operational efficiency of the shared e-scooter system after the implementation of policy. The usage efficiency is quantified by the number of trips per shared e-scooter. Collectively, these metrics support a descriptive analysis of the policy effect on shared e-scooter mobility.

4.4.2. System benefits used for model-based estimation

In addition to usage patterns of shared e-scooters, we also assessed the policy effects on system benefits through model-based estimation, primarily GHG emission reduction and travel time reduction. As shown in Fig. 2, this framework comprises three steps: extraction of trip-specific information, estimation of trip-specific mode substitution, and evaluation of GHG emission reductions and travel time reduction due to each SES trip. More details of the methodologies for assessing the system benefits of shared e-scooters in terms of GHG emission reduction and user travel time reductions are available in our previous study (Gao et al., 2024). This approach is based on three assumptions: (i) that the mode substitution patterns of general urban travelers are representative of those of e-scooter users; (ii) that these substitution patterns remain stable in the presence of e-scooter; and (iii) that they are invariant to the policy intervention.

The initial step in our analytical framework is to extract information on available alternative transport modes and their associated attributes, such as travel time and economic cost, for each SES trip, assuming SES does not exist. To facilitate this analysis, we employ the OpenTripPlanner (OTP), an open-source multimodal trip planning system, which supports comprehensive routing planning across different transportation modes. The data of specific trips including origin and destination coordinates, along with departure times, are employed to determine the shortest path across available transport modes. Then OPT outputs corresponding trip-specific information such as travel time, distance, economic cost for each OD pairs using five different modes including walking, cycling, private car, taxi and public transit (PT).

After gathering detailed trip-specific information on various transport modes, probabilities of available alternative transport modes are inferred using a multinomial logit model (MNL). This step is conducted under the assumption that no SES exist. Following the methodology outlined by Gao et al. (2024), the utility of selecting a particular transport mode is assessed based on three components including level-of-service attributes, factors that significantly influence passenger preferences and alternative-specific constants (ASC) for different transport mode. The detailed explanations of these factors can be derived from Gao et al. (2024).

Finally, the model-based system benefits estimation involves GHG emission reduction and travel time reduction. The difference of GHG emission from a same OD using SES and replaced transport mode is determined as emission reduction. Similarly, the difference of travel time by SES and replaced transport mode is defined as travel time reduction. We evaluating the changes in GHG emission reduction and travel time reduction by comparing them before and after the implement of SES policies. The detailed trip-level estimation procedure is provided in the Appendix.

5. Results and discussion

In this section, we begin by examining whether the policy affects shared e-scooter demand, using RDD analysis to determine the existence of a policy effect. We then quantify the impact of policy on usage patterns and system benefits through DoP analysis.

5.1. Causal analysis using RDD

To examine whether the policy influences SES, we conduct RDD analysis. MLM city has not been included in RDD analysis due to the lack of data for Friday before policy implementation. The incomplete weekly seasonality hinders reliable outcomes of RDD analysis. Consequently, we selected STH and GBG as representative cities to examine the effect of policy implementation on shared e-scooter demand.

We perform deseasonalization on the original data to eliminate the deviation caused by weekly seasonality. Fig. 3 represents the original data and deseasonalized data in STH and GBG. The horizontal axis represents dates, with 0 corresponding to the policy implementation date of September 1, 2022. Negative values indicate days before the policy implementation, and positive values indicate days after. Fig. 3 (a1, b1) shows the raw data for the number of trips over time. There are

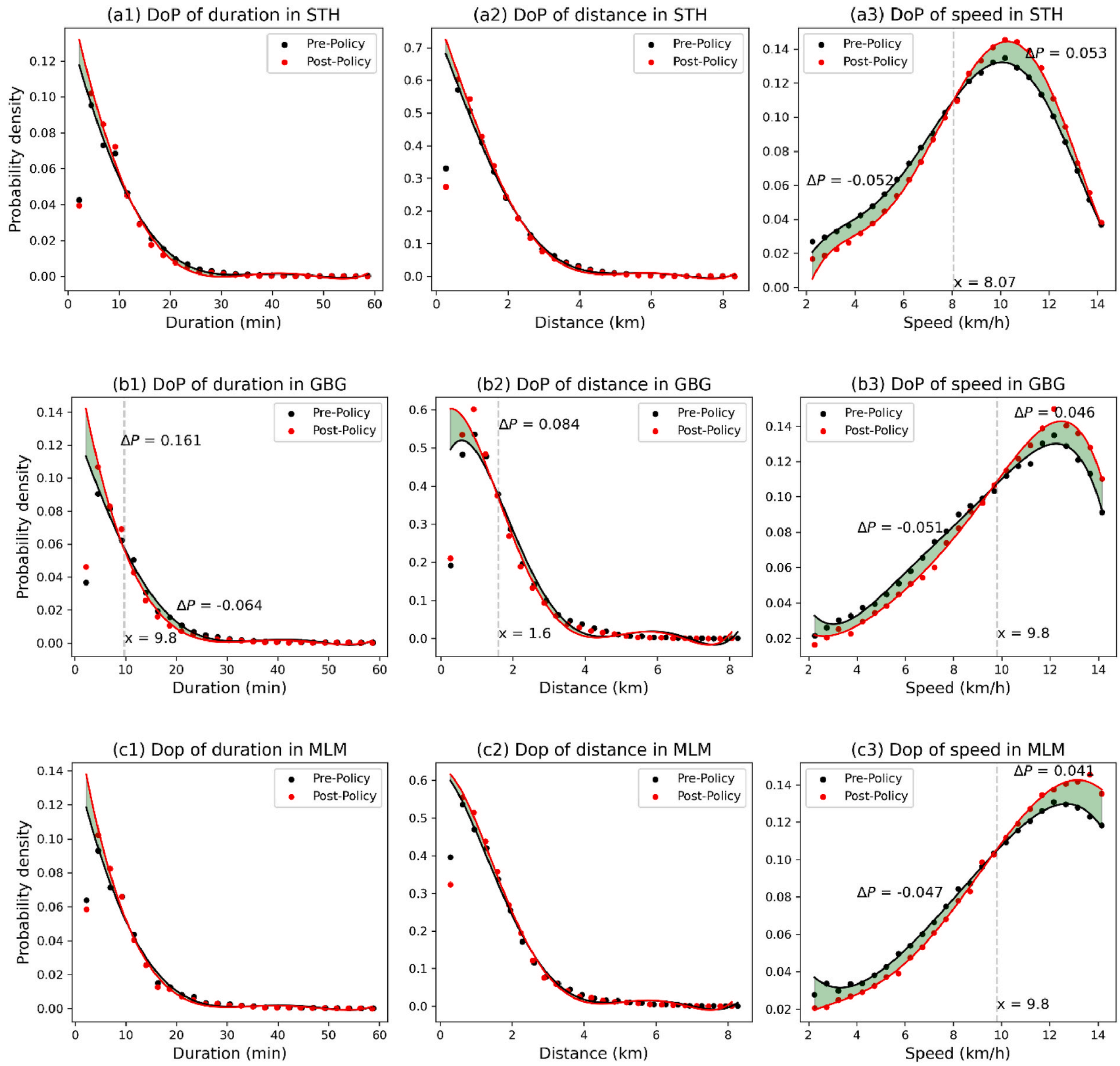

Fig. 6. The DoP results of trip characteristics.

significant fluctuations, suggesting weekly patterns. Particularly in STH, the number of trips ranges from approximately 8000 to 22,000 before the policy implementation, indicating high variability. After the policy implementation, there is a significant decrease in values, but the overall trend remains fluctuant. It is evident that the number of trips is reduced after the policy implementation. Fig. 3 (a2, b2) displays the number of trips after removing seasonality. Before the policy implementation, the deseasonalized number of trips is relatively stable with minor fluctuations. After the policy implementation, the number of trips stabilizes around lower values. The deseasonalized data provides a clearer comparison of the number of trips before and after the policy, facilitating a better understanding of policy effects.

Table 1 reports the RDD results for the policy effect on the number of trips in STH and GBG. Given substantial missing observations before August 7 2022, 25 days is the maximum reliable symmetric window for this dataset. To assess bandwidth sensitivity, we therefore estimate the model using symmetric windows of 7 days, 14 days, and 25 days around the policy cutoff. In both cities, the estimated discontinuity at the policy date is statistically significant across all three bandwidth specifications. We additionally conduct a placebo cutoff test at August 19 2022, the midpoint of the 25 days pre-policy period, using a 12 days window. The placebo estimates are not statistically significant in either city. The p-value is 0.147 in STH and 0.266 in GBG. This pattern indicates that the observed discontinuity is associated with the policy implementation date rather than a generic fluctuation in the time series. Nevertheless, given the short time window, the results reflect short-term effects around the policy date rather than long-term causal impacts.

5.2. Descriptive comparisons of usage patterns

In this section, we provide descriptive comparisons of e-scooter sharing policy on usage patterns, including demand, trip characteristics and usage efficiency.

5.2.1. Descriptive comparisons of demand

Fig. 4 displays trip patterns across three cities segmented by weekdays (Monday-Thursday), Fridays, and weekends. The data is shown both pre-policy and post-policy implementation. In all three cities, the policy implementation appears to have reduced the number of trips across weekdays, Fridays, and weekends. The most significant reductions in trips are observed during peak commuting hours, particularly in the mornings and evenings. STH shows the most pronounced

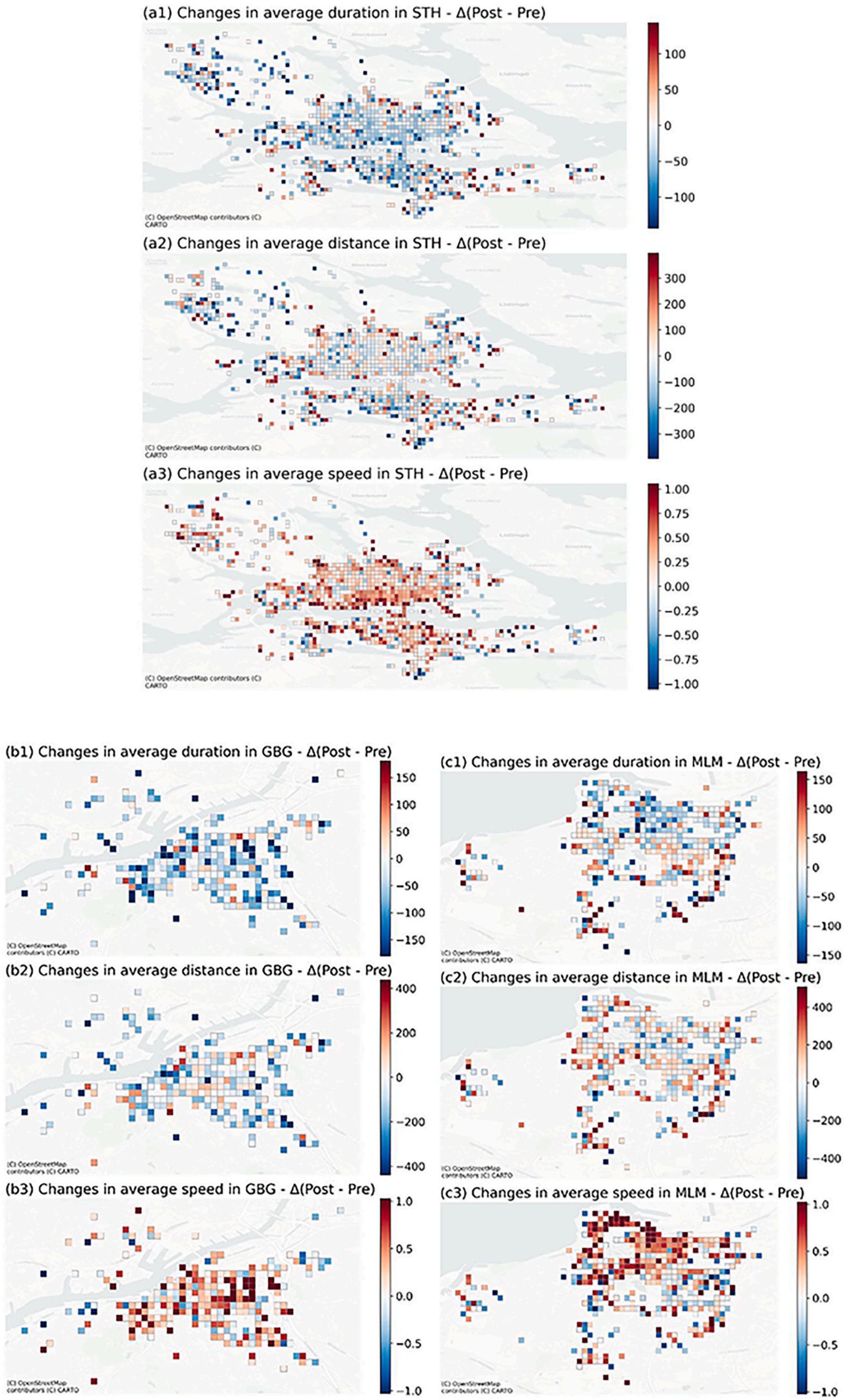

Fig. 7. Changes in spatial patterns of average duration (min), distance (km) and speed (km/h).

Table 3
t-test and K-S test results for usage efficiency.

		P value (*t*-test)	P value (KS test)	Mean (Pre-Policy)	Mean (Post-Policy)
STH	Total utilization frequency	0.000***	0.000***	78.164	98.640
	Daily utilization frequency	0.000***	0.000***	6.223	5.753
GBG	Total utilization frequency	0.000***	0.000***	38.866	27.801
	Daily utilization frequency	0.000***	0.000***	3.169	2.781
MLM	Total utilization frequency	0.000***	0.000***	21.061	25.911
	Daily utilization frequency	0.000***	0.000***	2.564	2.524

***, **, and * represent statistical significance at levels of 1%, 5% and 10%, respectively.

reduction in trips post-policy, followed by GBG. MLM shows some reductions, but the change is less consistent. Due the lack of data for Friday in MLM, we can only observe obvious reduction in trip numbers for weekdays and weekends. Additionally, the number of trips before and after policy implementation have the similar peak hour. Specifically, there are slight changes in temporal patterns of hourly demand. On weekdays and Friday, the morning peak is around 8 a.m. on weekday and Friday, while the evening peak is around 16:00-18:00. Notably, the pre-policy demand of Fridays in GBG differ from other days. This is because insufficient data was collected during that time period due to technical issues. On weekend, the demand has a pronounced evening peaks during 15:00-20:00 in three cities. Moreover, STH and MLM show a peak at 00:00. In MLM, the demand peak at 00:00 before the policy implementation even exceeds the demand at any other time during the week. In GBG, according to Voi's official availability schedule, shared e-scooters become available from 05:00 on weekends (https://www.voi.com/city/gothenburg). The prohibiting of riding shared e-scooter significantly reduces the demand during weekends.

Fig. 5 displays the changes in daily demand for shared e-scooter trips in three cities after the implementation of the policy. The color scales represent the change in the number of trips, with purple indicating a decrease and yellow indicating an increase. For STH in Fig. 5 (a), the map shows a mix of increases and decreases in demand across different areas. There are significant decreases in demand in several central areas, indicated by the darker purple colors. Some peripheral areas show slight increases in demand, as seen in the yellow and green patches. The policy likely led to a reduction in trips in the central areas of STH. For GBG in Fig. 5 (b), it shows a broader range of changes, with significant variations across different areas of the city. The darkest purple areas indicate substantial decreases in demand, with some areas experiencing drops of up to −1500 trips. There are also some areas with noticeable increases in demand, shown by the bright yellow areas. The policy had a more pronounced effect in GBG, causing substantial changes in trip demand. For MLM in Fig. 5 (c), it indicates changes that are less extreme than those in Gothenburg. The policy resulted in moderate changes in MLM, with both increases and decreases spread relatively evenly across the city.

5.2.2. *Descriptive comparisons of trip characteristics*

As shown in Table 2 t-test and K-S test results, duration, distance, and speed are all statistically significant in all three cities under both tests, with p values below 0.001. This indicates that policy implementation is associated with significant changes in both mean levels and overall distributional structure across STH, GBG, and MLM. For mean values, all three cities show shorter and faster trips after policy. Fig. 6 further shows where the policy-related distributional shifts occur within each city. Across all three cities, speed exhibits a consistent threshold effect. The probability of trips below the city-specific threshold decreases, while the probability above the threshold increases, indicating a clear post-policy shift from lower-speed trips to higher-speed trips. The threshold is around 8.07 km per hour in STH and around 9.8 km per hour in both GBG and MLM, with similar magnitudes of decline below and increase above the threshold. For duration and distance, the post-policy distributions also show threshold-based redistribution. In general, the probability shifts toward shorter durations and shorter distances, which is consistent with the mean reductions reported in Table 2. In GBG, where threshold points are more clearly identified, indicating a concentration toward shorter trips.

Fig. 7 analyzes the changes in average trip characteristics before and after the policy implementation for the three cities. Overall, most grids show a decrease in average trip duration and distance following policy implementation, indicating that the policy tends to reduce travel times and trip lengths across urban areas. In particular, more than half of the grids in all cities show reductions in duration and distance, with some cities exhibiting reductions in over 70% of grids. Conversely, average trip speed shows a consistent pattern of increase in the majority of grids across all cities, often exceeding 65% of grids. Detailly, for trip duration, the spatial changes are similar across all three cities. The changes are mixed, indicating that the policy had varying changes in trip duration across different areas of the cities. Some areas see an increase in average duration (yellow areas), while others see a decrease (purple areas). This variability may be due to changes in commuter behavior or the availability of alternative transportation options. For trip distance, the differences in average trip distance are slight in the city centers. In the suburbs, however, there are more areas with decreased distances, suggesting that the policy may lead to more localized trips, reducing the need for longer trips. For average speed, the changes are particularly noticeable in all three cities, suggesting that the policy may have influenced how fast to travel using shared e-scooters. There are significant increases in average speed, especially in the city centers, implying potential improvements in traffic conditions for shared e-scooters. In summary, the observed changes suggest that the policy has influenced trip characteristics differently under various urban contexts. In all three cities, the policy implementation generally leads to faster trips within city centers. Suburban areas show a tendency towards trips with shorter distance and sometimes faster speed.

5.2.3. *Descriptive comparisons of usage efficiency*

As shown in Table 3 t-test and K-S test results for usage efficiency, both total utilization frequency and daily utilization frequency are statistically significant in all three cities under both tests, with p values below 0.001. This indicates that policy implementation is associated with significant changes in both mean levels and distributional patterns of utilization efficiency. For total utilization frequency, the policy effect differs by city. STH shows an increase after policy, while both GBG and MLM show decreases. For daily utilization frequency, all three cities show post-policy decreases.

Fig. 8 further localizes these changes by threshold intervals. For total utilization frequency, STH shows two threshold points near 49.83 and 132.33. The probability decreases below 49.83, increases strongly between 49.83 and 132.33, and decreases again above 132.33, indicating a concentration in the middle range. GBG shows a threshold near 35.5, with increased probability below the threshold and decreased probability above it, consistent with a shift toward lower total utilization. MLM shows two thresholds near 9.36 and 45.53, with lower probability below 9.36, higher probability in the middle interval from 9.36 to 45.53, and slightly lower probability above 45.53. For daily utilization frequency, STH shows thresholds near 8.69 and 19.5, with increased probability below 8.69 and reduced probability above. GBG shows thresholds near 5.6 and 13.64, with increased probability at lower levels and clear declines in middle and higher ranges. MLM shows thresholds

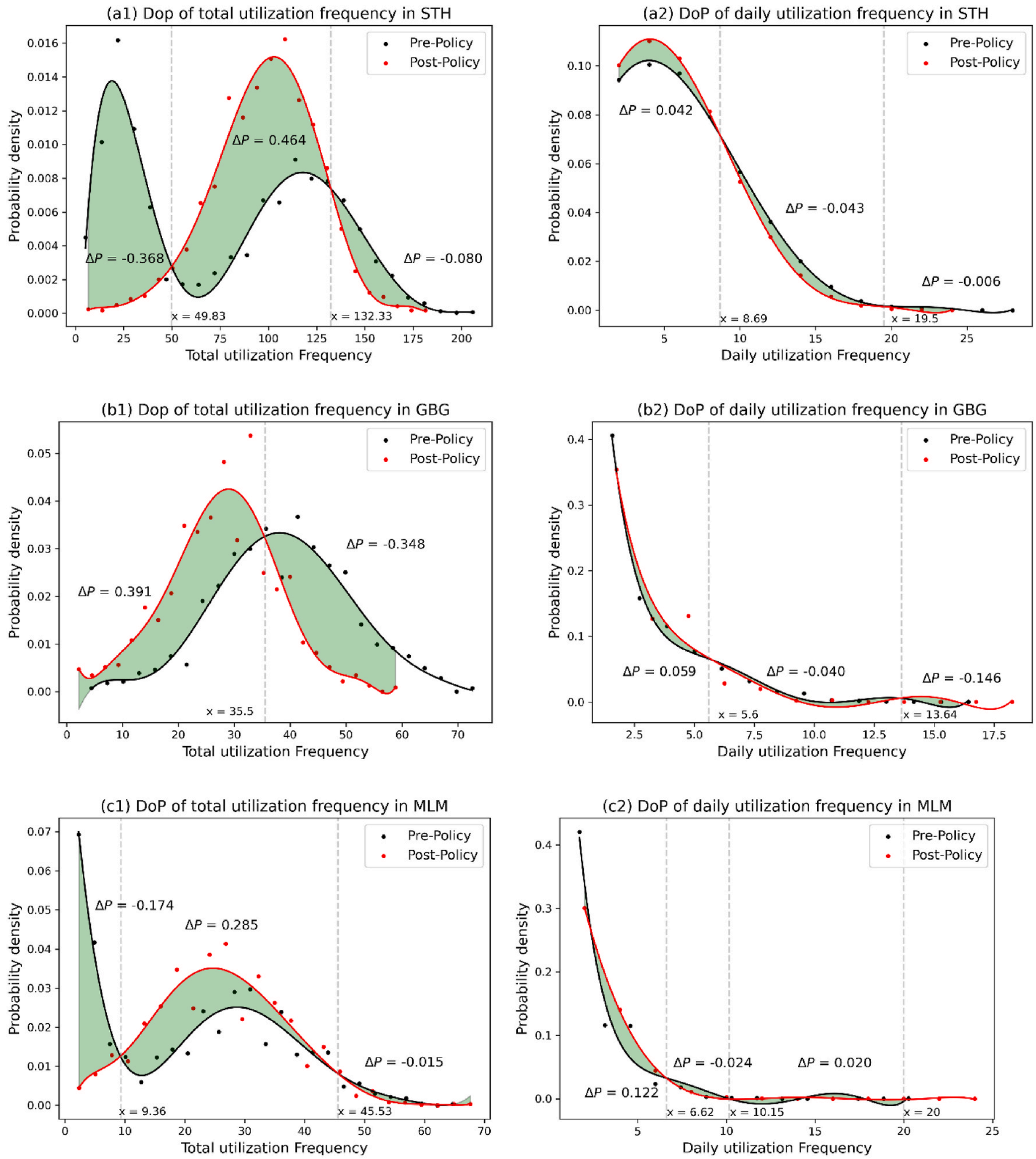

Fig. 8. The DoP results of utilization frequency.

near 6.62, 10.15, and 20, with increased probability in the lowest range and only minor redistribution in middle and upper intervals. These threshold patterns are also consistent with the post-policy decline in daily utilization means across all three cities.

5.3. *Model-based estimation of system benefits*

In this section, we provide model-based estimation of benefits, including time saving and GHG emission reduction.

5.3.1. *Model-based estimation of time saving*

As shown in Table 4 t-test and K-S test results for system benefits, time saving is statistically significant in all three cities under both tests, with p values below 0.001. Mean time saving increases after policy in all cities, from 9.273 to 9.683 min in STH, from 3.842 to 4.348 min in GBG, and from 6.838 to 7.431 min in MLM. This indicates a consistent post-policy improvement in per-scooter time-saving performance. Fig. 9 further shows how these improvements are distributed across intervals. In STH, two thresholds appear near 8.4 and 12 min. Probability decreases below 8.4 by about 0.128 and above 12 by about 0.034, while probability between 8.4 and 12 increases by about 0.183, indicating concentration in a moderate time-saving range. In GBG, a threshold near 4.5 min separates a decrease below the threshold and an increase above it, both with magnitude about 0.164, showing a clear shift toward higher time-saving values. In MLM, a similar pattern appears around 5.38 min, with probability decreasing below the threshold by about 0.114 and increasing above it by about 0.152. Overall, Table 4 confirms that time saving improves significantly, and Fig. 9 shows that this improvement is mainly driven by redistribution from lower to higher time-saving intervals.

Fig. 10 displays spatial changes in total time saving (a month) and average time saving (per trip) at aggregated level. Positive grids represent reductions in travel time, while negative grids indicate increases in travel time. For total time savings, the majority of grids in each city show

Table 4
t-test and K-S test results for system benefits.

		P value (*t*-test)	P value (KS test)	Mean (Pre-Policy)	Mean (Post-Policy)
STH	Time saving (min)	0.000***	0.000***	9.273	9.683
	GHG emission reduction(g)	0.000***	0.000***	−53.728	−54.162
GBG	Time saving (min)	0.000***	0.000***	3.842	4.348
	GHG emission reduction(g)	0.000***	0.010***	−63.280	−60.623
MLM	Time saving (min)	0.000***	0.000***	6.838	7.431
	GHG emission reduction(g)	0.000***	0.376	−39.337	−38.460

***, **, and * represent statistical significance at levels of 1%, 5% and 10%, respectively.

negative values, indicating that most areas experienced increased travel time after policy implementation. This pattern is especially evident in STH and MLM, where more than 60% of grids show negative changes. In GBG, the split is more balanced but still slightly favors negative grids. In contrast, the distribution of average time savings per e-scooter shows a more balanced or even positive trend. Over half of the grids in STH, GBG, and MLM display positive changes in average time savings, suggesting that many individual trips became faster following policy implementation. These results highlight that while the policy may have increased total travel time in many parts of cities, it appears to have improved the efficiency of individual trips in many areas.

5.3.2. Model-based estimation of GHG emission reduction

For GHG emission reduction, the policy effect is weaker and less consistent than for time saving. Table 4 shows that mean GHG reduction per trip changes in all three cities, but inferential results differ by city. In Table 4, the *t*-test results are significant for STH, GBG, and MLM, indicating statistically detectable changes in the mean level. However, the KS test is significant for STH and GBG, while it is non-significant for MLM. This suggests that in STH and GBG, the policy is associated with both mean-level changes and distributional shifts, whereas in MLM the effect is mainly reflected in a small average-level change. Fig. 11 provides further support for these findings. The pre-policy and post-policy distributions largely overlap in all three cities, indicating that the overall changes in GHG emission reduction are modest. Nevertheless, small local differences can be observed around the main peak and the tails, especially in STH and GBG, where both the *t*-test and KS test indicate statistically significant changes. In contrast, the MLM curves are almost indistinguishable, which is consistent with the non-significant KS test result.

Fig. 12 illustrates the spatial changes in both total (monthly) and average (per trip) GHG emission reductions across three cities. Positive grids represent greater GHG emission reduction, while negative grids indicate increased emissions. For total GHG emission reductions, most grids in all three cities exhibit positive changes after policy implementation. Specifically, more than 70% of grids in STH and more than 60% of grids in both GBG and MLM show positive changes, suggesting that the policy generally enhances total GHG emission reduction across a large portion of the urban areas. In contrast, the distribution of average GHG emission reductions per e-scooter is more balanced across the cities. In STH and GBG, more than half of the grids exhibit positive changes, indicating that in many areas, individual trips produce greater environmental benefits post-policy. However, in MLM, the split between positive and negative grids is almost equal, reflecting a more mixed effect on per-trip GHG emission reductions. Additionally, the average changes in emission reduction per trip vary across different urban contexts. Notably, there is a significant increase in emission reduction in the city centers (indicated in yellow).

5.3.3. Sensitivity analyses

The MNL model mainly considers three level-of-service attributes, including travel distance, travel time, and travel cost. Therefore, we

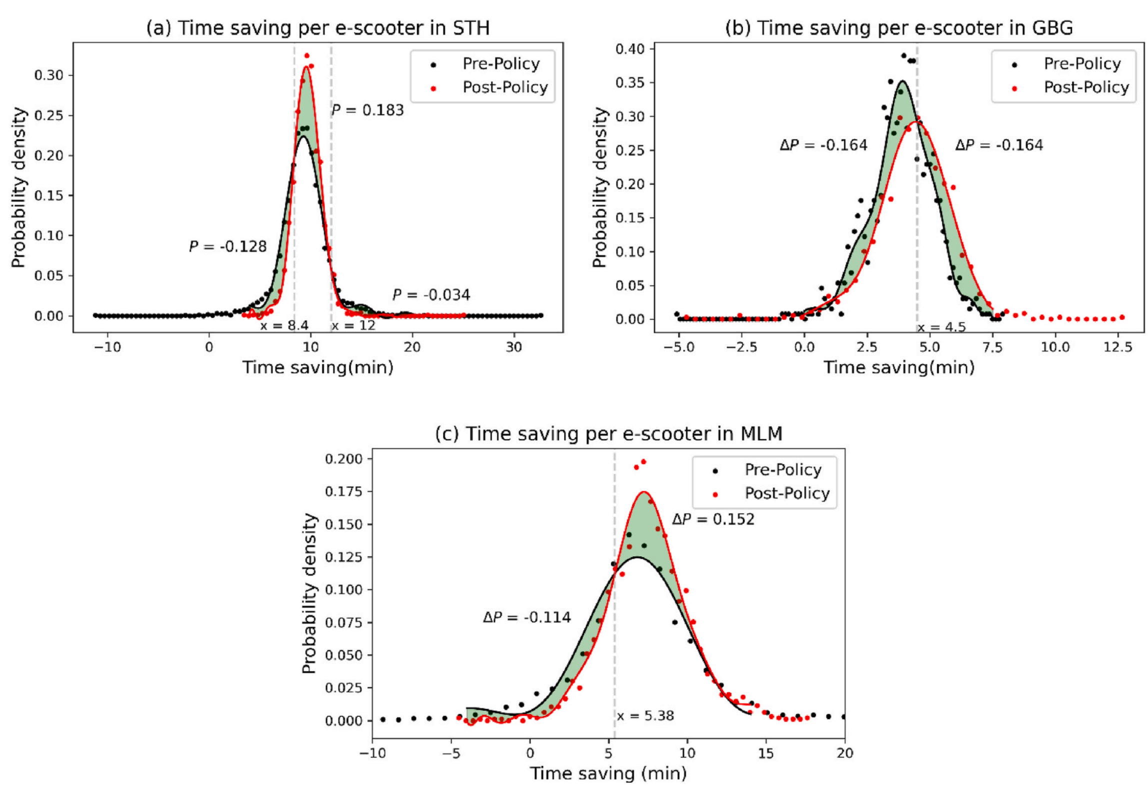

Fig. 9. The DoP results of time saving (per shared e-scooter).

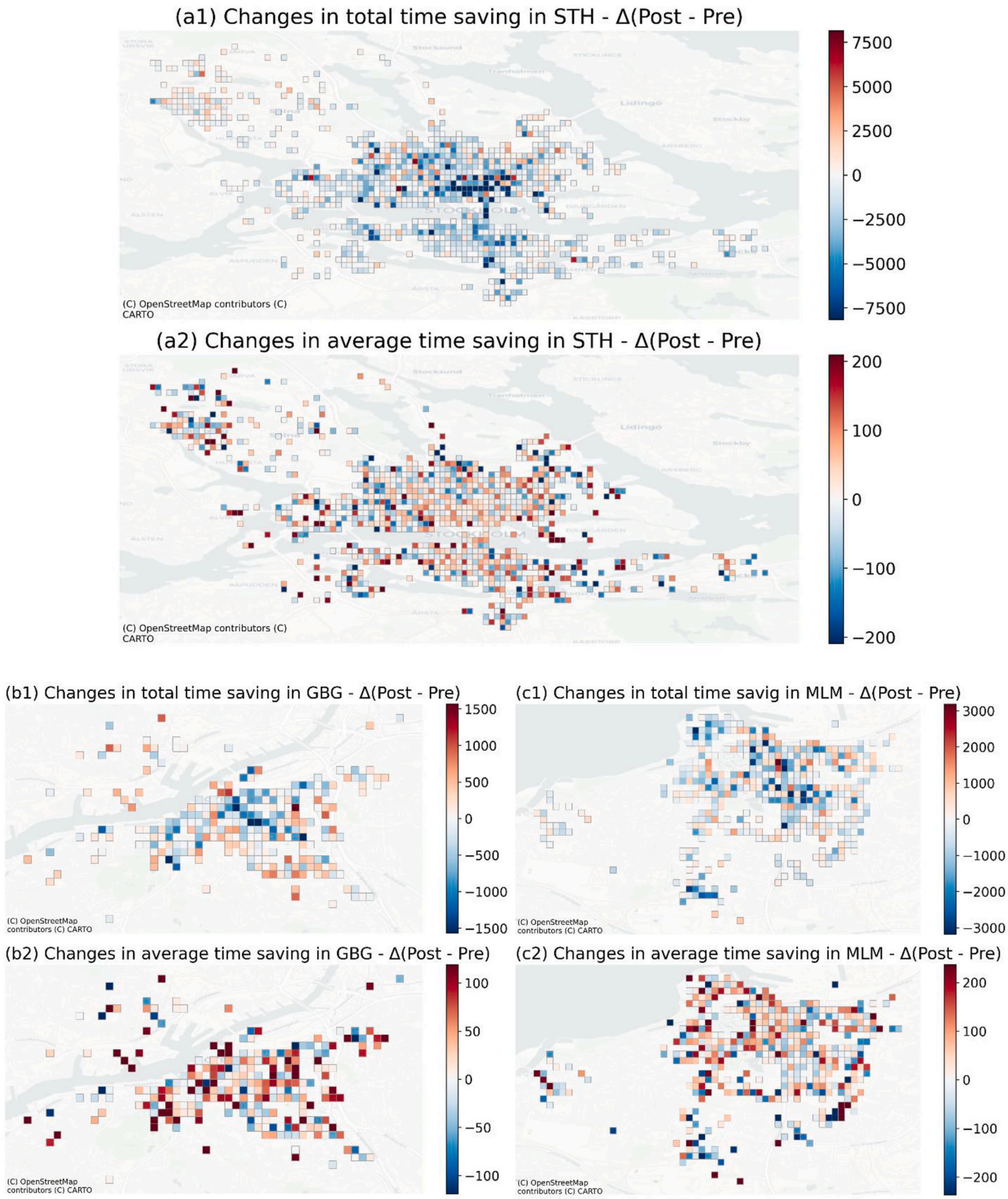

Fig. 10. Spatial patterns of changes in time saving.

conducted sensitivity analyses on the corresponding coefficients in the utility functions. Specifically, the distance coefficients for walking and biking, the time and cost coefficients for PT, and the time and cost coefficients for car and taxi were varied by −20%, −10%, +10%, and +20% around their baseline values. In the original MNL implementation, car and taxi share the same time coefficient, and they also share the same cost coefficient. Therefore, the car and taxi time coefficients were varied jointly, and the car and taxi cost coefficients were also varied jointly. For each scenario, the mode substitution probabilities were recalculated using the original MNL formulation, and the resulting changes in mean time saving and mean emission reduction were compared between the pre-policy and post-policy periods. As shown in Table 5, the results show that the estimated changes in mean time saving are highly stable across all tested parameter settings. The emission-reduction estimates are more sensitive in magnitude, especially to the walking-distance and PT-cost coefficients, but the main city-specific patterns remain unchanged. STH consistently shows a slightly negative change in mean emission reduction, whereas MLM and GBG remain positive across the tested scenarios.

In addition to the MNL parameter sensitivity analysis, we further examined the sensitivity of the emission reduction estimates to the life-cycle emission factors. The analysis focused on the emission factors used in the GHG calculation, including bike, PT, private car, taxi, and shared e-scooter. Each emission factor was varied by −20%, −10%, +10%, and +20% around its baseline value, while the MNL substitution probabilities and all other emission factors were kept unchanged. The reported values represent the post-policy minus pre-policy changes in mean emission reduction. As shown in Table 6, the estimated changes in

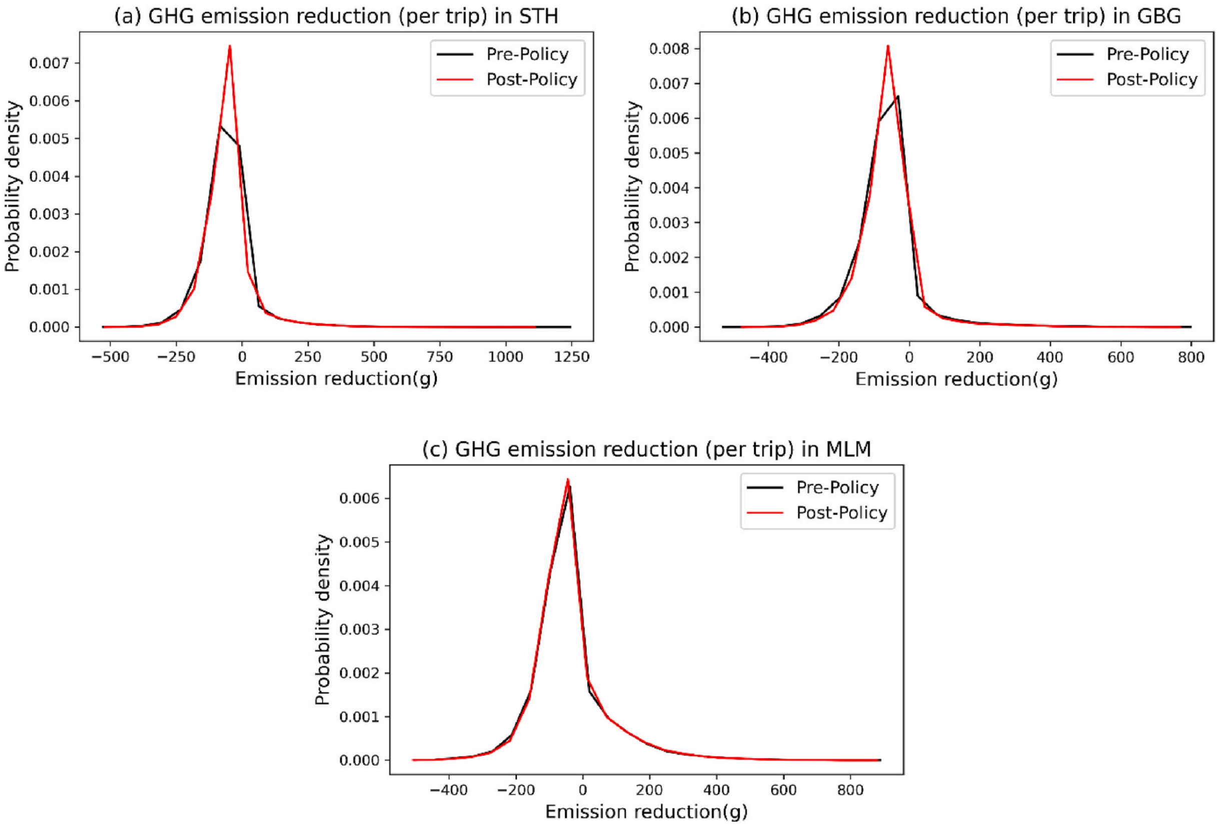

Fig. 11. The changes in GHG emission reduction.

emission reduction are generally stable across various tested emission factor scenarios. For STH, the change in mean emission reduction remains negative under all tested scenarios. In contrast, MLM and GBG consistently show positive changes in mean emission reduction across all emission factor variations. This indicates that the emission-reduction results are not driven by a single assumed emission factor.

6. Conclusions

This study proposes a comprehensive analytical framework that quantifies e-scooter sharing policy effects on usage patterns and system-level benefits by leveraging real-world before-and-after data. The framework synthesizes statistical techniques, RDD and DoP analysis, to rigorously evaluate policy effects on usage patterns, time savings, and greenhouse gas emission reductions. By utilizing empirical data from three Nordic cities, the approach captures realistic evaluation and ensures that the identified impacts are both statistically reliable and causally interpretable.

First, the RDD analysis confirms that policy implementation has a statistically significant effect on e-scooter demand at the 1% level, with consistent results observed across STH and GBG after deseasonalization. This validates that the policy indeed alters and reduces shared e-scooter usage.

Second, building upon the RDD results, the *t*-test, K-S test and DoP analysis reveal that the policy affects various dimensions of e-scooter usage and system performance with distinct spatial heterogeneity. In terms of demand, the policy reduces trip volumes across weekdays, Fridays, and weekends, with the most pronounced effects observed during peak commuting hours, particularly in STH and GBG. Spatial analysis further reveals that central urban areas tend to experience the greatest reductions in trip demand, while some peripheral areas show slight increases. Regarding trip characteristics, duration and distance decrease after policy implementation, while speed increases. The *t*-test and KS test are significant for these indicators, showing that the policy affects both average levels and distribution shapes. Grid-level analysis confirms that most urban areas experience decreased trip durations and distances, with more than half of the grids in all cities showing reductions. Conversely, the majority of grids exhibit increased trip speeds, suggesting improved operational efficiency following policy implementation. For utilization frequency, daily utilization decreases in all three cities, indicating lower short term turnover intensity. Total utilization shows city heterogeneity, increasing in STH and MLM but decreasing in GBG, which suggests different city level adaptation patterns under the same policy framework.

Third, in terms of system benefits, time saving increases significantly in all three cities, with consistent evidence from both *t*-test and KS test. GHG emission reduction is less consistent and more city specific. In STH and GBG, both the *t*-test and the KS test are significant, indicating changes in both the mean level and the distribution of GHG emission reduction. In MLM, the *t*-test is significant but the KS test is not significant, suggesting a modest mean-level change without a strong distributional shift. While total travel time increases in many urban areas, average time savings per trip improve in more than half of the grids in all cities, indicating that individual trips become more efficient despite the overall reduction in usage. For GHG emissions, the evidence is city specific. Overall, total reductions increase across most areas, especially in STH and GBG, suggesting that the policy generally enhances environmental benefits. However, the effects on average GHG emission reductions per trip are more mixed, with some areas benefiting and others not, highlighting the complex interplay between policy, usage patterns, and local urban contexts.

Beyond the specific Swedish case context, these findings contribute to broader debates on how shared micromobility should be governed under heterogeneous urban conditions. The results suggest that policy effectiveness is not only a question of whether demand is reduced, but also how changes are distributed across time periods, locations, and

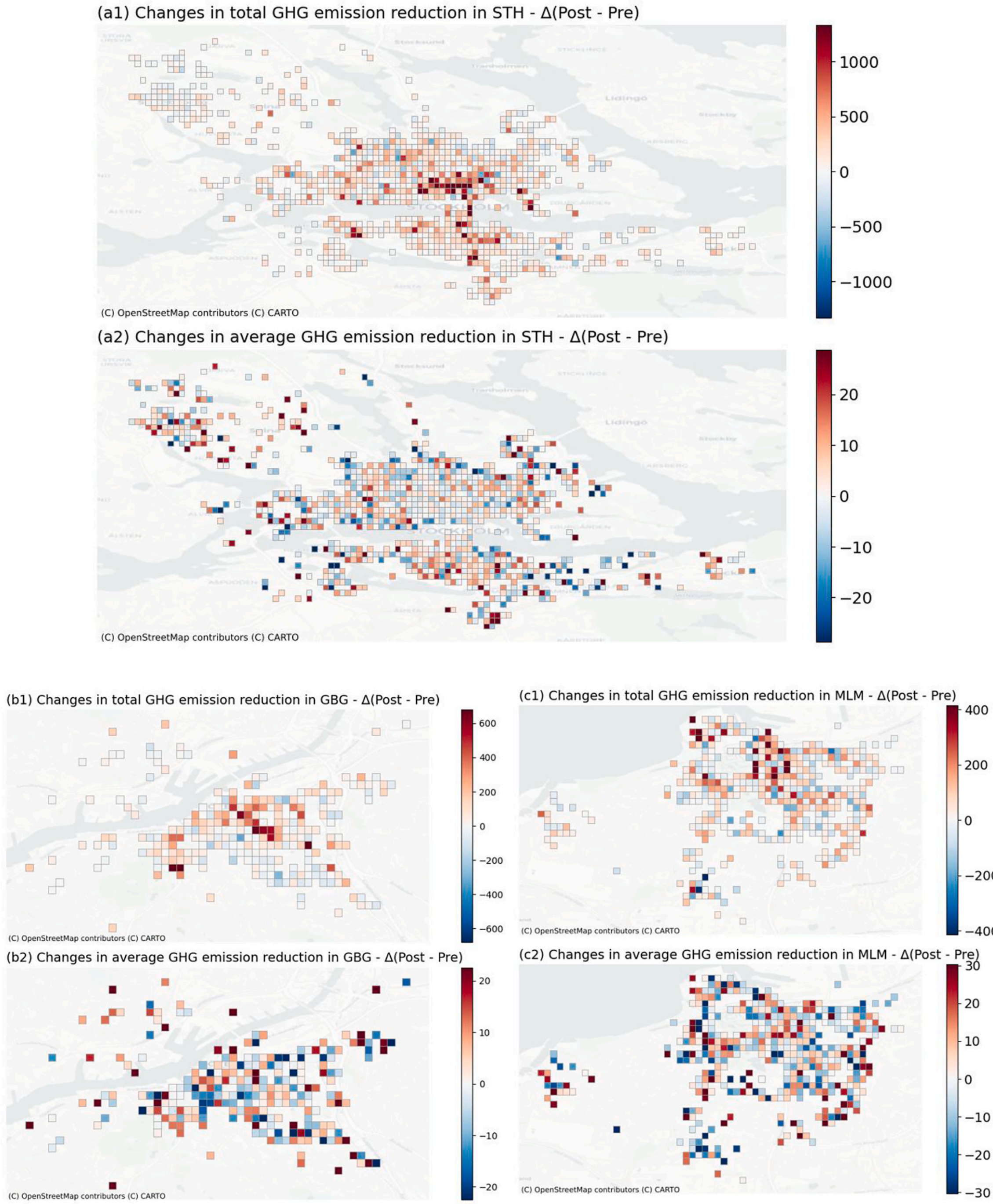

Fig. 12. Spatial patterns of GHG emission reduction (g).

system performance dimensions. This also highlights the relevance to evidence-based policy design, suggesting that context sensitive and multidimensional evaluation is necessary to avoid unified regulation. More broadly, the integrated framework used in this study offers a transferable approach for assessing policy effects on both usage patterns and system-level outcomes in other cities and mobility systems. Additionally, beyond a purely efficiency-oriented interpretation, our findings may also be understood within a broader human centered transition perspective. The observed improvements in system performance, reliability, and user related outcomes indicate that the policy may help create a more stable, predictable, and less cognitively demanding mobility environment. In this sense, the effects of the policy should not be understood solely in terms of operational optimization, but also in terms of improved user experience, perceived comfort, reduced travel uncertainty, enhanced convenience, and potentially stronger long-term user acceptance of shared e scooter systems. More broadly, this interpretation highlights that the evaluation of shared micromobility policies should consider not only aggregate system efficiency, but also user adaptation and the wider implications for sustainable urban mobility governance.

These findings collectively demonstrate the importance of adopting context-sensitive policy measures that address not only overall usage but also specific trip characteristics and environmental outcomes. The integrated RDD and DoP framework developed in this study provides a multi-dimensional approach for evaluating shared mobility policies using real-world data. This methodological contribution enables

Table 5
Sensitivity analysis for parameters in MNL (Post - Pre).

Parameter	Change in parameter	Changes in mean time saving(mins)			Changes in mean emission reduction(g)		
		STH	MLM	GBG	STH	MLM	GBG
$\beta_{walk\_dis\tan ce}$	−20%	0.408	0.593	0.431	−0.444	0.716	3.269
	−10%	0.409	0.593	0.470	−0.439	0.796	2.950
	+0%	0.410	0.593	0.506	−0.434	0.877	2.657
	+10%	0.412	0.591	0.539	−0.428	0.957	2.389
	+20%	0.413	0.589	0.569	−0.420	1.032	2.147
$\beta_{cycling\_dis\tan ce}$	−20%	0.409	0.590	0.505	−0.434	0.877	2.646
	−10%	0.410	0.591	0.505	−0.434	0.877	2.651
	+0%	0.410	0.593	0.506	−0.434	0.877	2.657
	+10%	0.411	0.593	0.506	−0.434	0.878	2.663
	+20%	0.411	0.594	0.506	−0.433	0.879	2.669
β_{PT_time}	−20%	0.413	0.595	0.513	−0.425	0.870	2.708
	−10%	0.412	0.594	0.509	−0.429	0.874	2.682
	+0%	0.410	0.593	0.506	−0.434	0.877	2.657
	+10%	0.408	0.591	0.502	−0.438	0.882	2.632
	+20%	0.407	0.589	0.498	−0.443	0.885	2.608
$\beta_{PT\_\cos t}$	−20%	0.415	0.603	0.535	−0.420	0.863	2.798
	−10%	0.413	0.598	0.520	−0.426	0.870	2.726
	+0%	0.410	0.593	0.506	−0.434	0.877	2.657
	+10%	0.408	0.587	0.491	−0.442	0.886	2.591
	+20%	0.405	0.581	0.477	−0.451	0.895	2.528
$\beta_{car\_time}/\beta_{taxi\_time}$	−20%	0.410	0.592	0.506	−0.440	0.888	2.623
	−10%	0.410	0.592	0.506	−0.437	0.883	2.640
	+0%	0.410	0.593	0.506	−0.434	0.877	2.657
	+10%	0.410	0.593	0.505	−0.431	0.873	2.674
	+20%	0.410	0.593	0.505	−0.428	0.868	2.691
$\beta_{car\_\cos t}/\beta_{taxi\_\cos t}$	−20%	0.410	0.591	0.510	−0.437	0.914	2.448
	−10%	0.410	0.592	0.508	−0.435	0.895	2.567
	+0%	0.410	0.593	0.506	−0.434	0.877	2.657
	+10%	0.410	0.593	0.504	−0.431	0.863	2.726
	+20%	0.410	0.593	0.503	−0.428	0.849	2.782

Table 6
Sensitivity analysis for emission factors (Post - Pre).

	Change in parameter	Changes in mean emission reduction(g)		
		STH	MLM	GBG
EF_{bike}	−20%	−0.435	0.878	2.713
	−10%	−0.434	0.878	2.685
	+0%	−0.434	0.877	2.657
	+10%	−0.433	0.877	2.628
	+20%	−0.433	0.877	2.600
EF_{PT}	−20%	−0.421	0.886	2.832
	−10%	−0.427	0.882	2.744
	+0%	−0.434	0.877	2.657
	+10%	−0.440	0.874	2.569
	+20%	−0.446	0.870	2.482
EF_{car}	−20%	−0.446	0.761	3.446
	−10%	−0.440	0.819	3.052
	+0%	−0.434	0.877	2.657
	+10%	−0.428	0.936	2.262
	+20%	−0.421	0.995	1.867
EF_{taxi}	−20%	−0.437	0.875	2.680
	−10%	−0.435	0.877	2.669
	+0%	−0.434	0.877	2.657
	+10%	−0.432	0.879	2.645
	+20%	−0.431	0.881	2.633
$EF_{e-scooter}$	−20%	−0.343	0.813	1.080
	−10%	−0.388	0.846	1.868
	+0%	−0.434	0.877	2.657
	+10%	−0.479	0.910	3.445
	+20%	−0.524	0.943	4.233

policymakers and urban planners to design and implement more effective and sustainable urban transportation systems. Nevertheless, this study has several limitations that warrant consideration. First, while the analysis leverages real-world data and integrates rigorous statistical methods to control for confounding factors, it cannot fully account for all unobserved variables that may influence e-scooter usage patterns and system benefits. Second, the data is limited to three Swedish cities, which, although diverse in certain urban characteristics, may not fully represent the wide range of urban contexts in other regions or countries. Future research could expand this analysis to additional cities with different policy designs and mobility cultures and explore complementary methods such as qualitative surveys or interviews to enrich the understanding of user responses to e-scooter sharing policies. Third, some outcomes, such as time savings and GHG effects, are model derived rather than directly observed. These estimates depend on assumptions in the mode replacement component and on average LCA factors. The current dataset does not provide sufficiently detailed parameter distribution information to fully propagate uncertainty for LCA factors. Once more detailed data become available, these uncertainties can be better calibrated and propagated through the framework. Fourth, the approach used to estimate system benefits is based on several key assumptions rather than being directly identified from empirical mode-switching data, a limitation that has also been recognized in our and related prior studies (Gao et al., 2023, 2024; Reck et al., 2022; Zhou et al., 2023). However, as more detailed data become available, especially observed mode-shift data after policy implementation, these deviations can be better calibrated and reduced. This is also an important direction for future work.

CRediT authorship contribution statement

Zhe Zhang: Formal analysis, Investigation, Methodology, Validation, Visualization, Writing – original draft, Writing – review & editing. **Ruo Jia:** Data curation, Investigation, Methodology, Validation, Writing – review & editing. **Yuan Liao:** Validation, Writing – review & editing. **Marina Wiemers:** Formal analysis, Methodology, Visualization. **Ying Yang:** Investigation, Methodology, Validation, Writing – review & editing. **Zhong-Ren Peng:** Validation, Writing – review & editing. **Kun Gao:** Conceptualization, Formal analysis, Funding acquisition, Methodology, Supervision, Validation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This study was partially funded by DriveSweden and VINNOVA through the project DipCOM (2024-02399) and Area of Advance Transport at Chalmers University of Technology.

Appendix

In MNL model, the utility of selecting a specific transport mode m for a trip is determined as

$$\begin{aligned} U_{walk} &= \beta_{walk\_distance} d_{walk\_distance} + ASC_{walk} \\ U_{cycling} &= \beta_{cycling\_distance} d_{cycling\_distance} + ASC_{cycling} \\ U_{PT} &= \beta_{PT\_time} t_{PT\_time} + \beta_{PT\_cost} c_{PT\_cost} + \beta_{inner} x_{inner} + \beta_{PT\_card} x_{PT\_card} \\ U_{car} &= \beta_{car\_time} t_{car\_time} + \beta_{car\_cost} c_{car\_cost} + \beta_{license} x_{license} + \beta_{male} x_{male} + \beta_{ownership} x_{ownership} + ASC_{car} \\ U_{taxi} &= \beta_{taxi\_time} t_{taxi\_time} + \beta_{taxi\_cost} c_{taxi\_cost} + \beta_{male} x_{male} + ASC_{taxi} \end{aligned} \tag{4}$$

The detailed explanations of these factors and their corresponding parameters can be derived from Gao et al. (2024). The probability of choosing a specific transport mode P_m is defined as

$$P_m = \frac{e^{AV_m \times U_m}}{\sum_{m=1}^{5} e^{AV_m \times U_m}} \tag{5}$$

where AV_m denotes the availability of transport mode m for a specific OD, which can also be obtained from section 4.2.1. If it is available, $AV_m = 1$. Otherwise, $AV_m = 0$.

For a specific transport mode, the estimation of GHG emission is conducted by the Life Cycle Analysis approach. This comprehensive approach examines emissions across different stages of the system's life cycle, encompassing production, operation, and disposal phases. Emission factors, represented in $CO_{2\text{-eq}}$ per passenger per kilometer, play a pivotal role in calculating the total emissions for a trip. By leveraging these factors, the emissions associated with a trip for OD pair i using a particular transport mode m can be precisely quantified, which is determined by

$$E_m^i = EF_m \times d_m^i. \tag{6}$$

EF_m denotes emission factor of transport mode m. The emission factors for walking, cycling, PT, private car, taxi, and shared e-scooter, as reported in a previous study conducted in London (Cottell et al., 2021), are 0, 37.05, 16.04, 160.7, 160.7, and 67.1, respectively. We hypothesize that these emission factors remain consistent when applied to similar urban environments, such as Stockholm, Gothenburg, and Malmö. d_m^i denotes distance of a trip for OD pair i using a particular transport mode m.

The emission E_{SES}^i resulting from the trip for OD pair i using SES is determined by multiplying the distance d_{SES}^i traveled for that trip by the emission factor EF_{SES}. However, when calculating the emission for the trip using alternative transport modes, we employ an average estimation derived from the sum of the probabilities of all available options.

$$E_{replaced}^i = \sum_{m=1}^{5} P_m \times E_m^i \tag{7}$$

The GHG emission reduction of trip for OD pair i is determined as

$$E_{reduction}^i = E_{replaced}^i - E_{SES}^i. \tag{8}$$

We have employed a comparable rationale to define the reduction in travel time. For OD pair i, the travel time of the trip using alternative transport modes is defined as the average value.

$$TT_{replaced}^i = \sum_{m=1}^{5} P_m \times TT_m^i \tag{9}$$

TT_m^i represent the travel time of a trip for OD pair i using a specific transport mode m. The travel time reduction is determined as

$$TT_{reduction}^i = TT_{replaced}^i - TT_{SES}^i. \tag{10}$$

TT_{SES}^i represents the travel time of the trip for OD pair i using e-scooter sharing.

Data availability

Data will be made available on request.

References

Abduljabbar, R.L., Liyanage, S., Dia, H., 2021. The role of micro-mobility in shaping sustainable cities: a systematic literature review. Transport. Res. Transport Environ. 92, 102734.

Abouelela, M., Chaniotakis, E., Antoniou, C., 2023. Understanding the landscape of shared-e-scooters in North America; Spatiotemporal analysis and policy insights. Transport. Res. Pol. Pract. 169, 103602.

Almaskati, D., Kermanshachi, S., Pamidimukkala, A., 2024. Convergence of emerging transportation trends: a comprehensive review of shared autonomous vehicles. Journal of Intelligent and Connected Vehicles 7 (3), 177–189.

Bach, X., Marquet, O., Miralles-Guasch, C., 2023. Assessing social and spatial access equity in regulatory frameworks for moped-style scooter sharing services. Transp. Policy 132, 154–162.

Badia, H., Jenelius, E., 2023. Shared e-scooter micromobility: review of use patterns, perceptions and environmental impacts. Transp. Rev. 43 (5), 811–837.

Button, K., Frye, H., Reaves, D., 2020. Economic regulation and E-scooter networks in the USA. Res. Transport. Econ. 84, 100973.

CNN, 2018. That electric scooter might be fun. It Also might be Deadly. Available at: https://edition.cnn.com/2018/09/29/health/scooter-injuries/index.html. (Accessed 3 July 2025).

Cottell, J., Connelly, K., Harding, C., 2021. Micromobility in London. Centre for, London. Retrieved. (Accessed 14 December 2022).

Emami, E., Ramezani, M., 2024. Integrated operator and user-based rebalancing and recharging in dockless shared e-micromobility systems. Communications in Transportation Research 4, 100155.

Fuady, S.N., Pfaffenbichler, P.C., Susilo, Y.O., 2024. Bridging the gap: toward a holistic understanding of shared micromobility fleet development dynamics. Communications in Transportation Research 4, 100149.

Gao, K., Jia, R., Liao, Y., Liu, Y., Najafi, A., Attard, M., 2024. Big-data-driven approach and scalable analysis on environmental sustainability of shared micromobility from trip to city level analysis. Sustain. Cities Soc. 115, 105803.

Gao, K., Li, A., Liu, Y., Gil, J., Bie, Y., 2023. Unraveling the mode substitution of dockless bike-sharing systems and its determinants: a trip level data-driven interpretation. Sustain. Cities Soc. 98, 104820.

Gössling, S., 2020. Integrating e-scooters in urban transportation: problems, policies, and the prospect of system change. Transport. Res. Transport Environ. 79, 102230.

Gu, Y., Chen, A., Jang, S., Kitthamkesorn, S., 2024. A binary choice model for adoption of an emerging travel mode with unique service features. Communications in Transportation Research 4, 100121.

Guo, Y., Zhang, Y., 2021. Understanding factors influencing shared e-scooter usage and its impact on auto mode substitution. Transp. Res., Part D Transp. Environ. 99, 102991.

Hong, B., Bonczak, B.J., Gupta, A., Kontokosta, C.E., 2021. Measuring inequality in community resilience to natural disasters using large-scale mobility data. Nat. Commun. 12 (1), 1870.

Huo, J., Yang, H., Li, C., Zheng, R., Yang, L., Wen, Y., 2021. Influence of the built environment on E-scooter sharing ridership: a tale of five cities. J. Transport Geogr. 93, 103084.

Janikian, G.S., Caird, J.K., Hagel, B., Reay, G., 2024. A scoping review of E-scooter safety: delightful urban slalom or injury epidemic? Transport. Res. F Traffic Psychol. Behav. 101, 33–58.

Janssen, C., Barbour, W., Hafkenschiel, E., Abkowitz, M., Philip, C., Work, D.B., 2020. City-to-city and temporal assessment of peer city scooter policy. Transp. Res. Rec. 2674 (7), 219–232.

Kazemzadeh, K., Haghani, M., Sprei, F., 2023. Electric scooter safety: an integrative review of evidence from transport and medical research domains. Sustain. Cities Soc. 89, 104313.

Kazemzadeh, K., Sprei, F., 2024. The effect of shared e-scooter programs on modal shift: evidence from Sweden. Sustain. Cities Soc. 101, 105097.

Kim, M., Puczkowskyj, N., MacArthur, J., Dill, J., 2023. Perspectives on e-scooters use: a multi-year cross-sectional approach to understanding e-scooter travel behavior in Portland, Oregon. Transport. Res. Pol. Pract. 178, 103866.

Latinopoulos, C., Patrier, A., Sivakumar, A., 2021. Planning for e-scooter use in metropolitan cities: a case study for Paris. Transport. Res. Transport Environ. 100, 103037.

Lei, Y., Ozbay, K., 2021. A robust analysis of the impacts of the stay-at-home policy on taxi and Citi Bike usage: a case study of Manhattan. Transp. Policy 110, 487–498.

Ma, Q., Yang, H., Ma, Y., Yang, D., Hu, X., Xie, K., 2021a. Examining municipal guidelines for users of shared E-Scooters in the United States. Transport. Res. Transport Environ. 92, 102710.

Ma, Q., Yang, H., Mayhue, A., Sun, Y., Huang, Z., Ma, Y., 2021b. E-Scooter safety: the riding risk analysis based on mobile sensing data. Accid. Anal. Prev. 151, 105954.

Mehzabin Tuli, F., Mitra, S., Crews, M.B., 2021. Factors influencing the usage of shared E-scooters in Chicago. Transport. Res. Pol. Pract. 154, 164–185.

Miljöbarometern, 2022. Stockholm environmental monitoring platform : 2022 weather data. Available at: https://miljobarometern.stockholm.se/. (Accessed 3 July 2025).

Mitropoulos, L., Stavropoulou, E., Tzouras, P., Karolemeas, C., Kepaptsoglou, K., 2023. E-scooter micromobility systems: review of attributes and impacts. Transp. Res. Interdiscip. Perspect. 21, 100888.

Mobility Foresights, 2021. Electric scooter sharing market in US and Europe 2021-2026. Market research report. Available at: https://mobilityforesights.com/product/scooter-sharing-market-report/. (Accessed 3 July 2025).

NACTO, 2020. Shared micromobility in the US: 2019. National Association of City Transportation Officials. Available at: https://nacto.org/wp-content/uploads/2020/08/2020bikesharesnapshot.pdf. (Accessed 3 July 2025).

Nikiforiadis, A., Paschalidis, E., Stamatiadis, N., Paloka, N., Tsekoura, E., Basbas, S., 2023. E-scooters and other mode trip chaining: preferences and attitudes of university students. Transport. Res. Pol. Pract. 170, 103636.

Oluwajana, S.D., Wang, C.M., 2023. Rationale for governance and effective guidelines towards attainment of shared e-scooter micromobility benefits in Windsor, Ontario. Case Stud. Transp. Policy 13, 101051.

Reck, D.J., Martin, H., Axhausen, K.W., 2022. Mode choice, substitution patterns and environmental impacts of shared and personal micro-mobility. Transport. Res. Transport Environ. 102, 103134.

Riggs, W., Kawashima, M., Batstone, D., 2021. Exploring best practice for municipal e-scooter policy in the United States. Transport. Res. Pol. Pract. 151, 18–27.

Roig-Costa, O., Miralles-Guasch, C., Marquet, O., 2024. Shared bikes vs. private e-scooters. Understanding patterns of use and demand in a policy-constrained micromobility environment. Transp. Policy 146, 116–125.

Salas-Niño, L., 2022. Analysis of current e-scooter safety regulation in a large US city using epidemiological components as a framework. Transp. Res. Rec. 2676 (10), 163–172.

Schlaff, C.D., Sack, K.D., Elliott, R.-J., Rosner, M.K., 2019. Early experience with electric scooter injuries requiring neurosurgical evaluation in District of Columbia: a case series. World Neurosurg. 132, 202–207.

Scooters, Unagi, 2019. The Comprehensive Guide to Electric Scooter Laws. Unagi Scooters. Available at: https://blog.unagiscooters.com/2019/10/15/the-comprehensive-guide-to-electric-scooter-laws/. (Accessed 3 July 2025).

Sexton, E.G., Harmon, K.J., Sanders, R.L., Shah, N.R., Bryson, M., Brown, C.T., Cherry, C. R., 2023. Shared e-scooter rider safety behaviour and injury outcomes: a review of studies in the United States. Transp. Rev. 43 (6), 1263–1285.

Sokolowski, M.M., 2020. Laws and policies on electric scooters in the european union: a ride to the micromobility directive? Eur. Environ. Law Rev. 29 (4).

Statistikmyndigheten SCB, 2024. Population statistics. Available at: https://www.scb.se/en/finding-statistics/statistics-by-subject-area/population/population-composition/population-statistics/. (Accessed 3 July 2025).

The Guardian, 2019. Invasion of the electric scooter: can our cities cope? Available at: https://www.theguardian.com/cities/2019/jul/15/invasion-electric-scooter-backlash. (Accessed 3 July 2025).

Trivedi, T.K., Liu, C., Antonio, A.L.M., Wheaton, N., Kreger, V., Yap, A., Schriger, D., Elmore, J.G., 2019. Injuries associated with standing electric scooter use. JAMA Netw. Open 2 (1) e187381-e187381.

Turoń, K., Czech, P., 2020. The concept of rules and recommendations for riding shared and private e-scooters in the road network in the light of global problems. In: Modern Traffic Engineering in the System Approach to the Development of Traffic Networks: 16Th Scientific and Technical Conference" Transport Systems. Theory and Practice 2019", 16. Springer, pp. 275–284. Selected Papers.

Vernon, N., Maddu, K., Hanna, T.N., Chahine, A., Leonard, C.E., Johnson, J.-O., 2020. Emergency department visits resulting from electric scooter use in a major southeast metropolitan area. Emerg. Radiol. 27, 469–475.

Yang, H., Ma, Q., Wang, Z., Cai, Q., Xie, K., Yang, D., 2020. Safety of micro-mobility: analysis of E-Scooter crashes by mining news reports. Accid. Anal. Prev. 143, 105608.

Yao, B., Qi, Z., Liu, Z., Zhu, M., Cui, S., Precup, R.-E., Roman, R.-C., 2025. Evaluating the sustainability of electric buses during operation via field data. Journal of Intelligent and Connected Vehicles 8 (3), 9210061.

Zakhem, M., Smith-Colin, J., 2024. An E-scooter route assignment framework to improve user safety, comfort and compliance with city rules and regulations. Transport. Res. Pol. Pract. 179, 103930.

Zhang, W., Buehler, R., Broaddus, A., Sweeney, T., 2021. What type of infrastructures do e-scooter riders prefer? A route choice model. Transport. Res. Transport Environ. 94, 102761.

Zhang, Z., He, H.-D., Yang, J.-M., Wang, H.-W., Xue, Y., Peng, Z.-R., 2022. Spatiotemporal evolution of NO2 diffusion in Beijing in response to COVID-19 lockdown using complex network. Chemosphere 293, 133631.

Zheng, Y., Meredith-Karam, P., Stewart, A., Kong, H., Zhao, J., 2023. Impacts of congestion pricing on ride-hailing ridership: evidence from Chicago. Transport. Res. Pol. Pract. 170, 103639.

Zhou, Y., Yu, Y., Wang, Y., He, B., Yang, L., 2023. Mode substitution and carbon emission impacts of electric bike sharing systems. Sustain. Cities Soc. 89, 104312.