The Dual and Asymmetric Impact of E-Scooters on Shared Mobility, Retailing, and Consumer Safety

Ruichun Liu and Unnati Narang*

Abstract

Shared micromobility services have grown rapidly in recent years. Within micromobility, electric scooters (e-scooters) have expanded in usage and account for 63% of shared micromobility trips in the U.S. While research in marketing has examined how e-scooters affect restaurant spending, their effects on firms, consumers, and society beyond the restaurant industry are unclear. Using the quasi-experimental entry of e-scooters in parts of Chicago in 2019, we examine how e-scooters impact other shared mobility (i.e., rideshare and bikeshare trips), retail visits (i.e., visits to restaurants and retail stores), and consumer safety (i.e., crimes and crashes). The results from a difference-in-differences analysis reveal the dual impact of e-scooters; while the entry of e-scooters improves economic activity, it adversely impacts consumer safety and other forms of micromobility. First, the entry of e-scooters increases the number of short rideshare trips by 3.01%, but decreases the number of bikeshare trips by 24.98% in the 18 weeks after the entry of e-scooters. Second, the entry of e-scooters increases consumer visits to restaurants by 1.77% and retail stores by 8.37%. Third, the entry of e-scooters increases the number of crimes (e.g., break-ins) by 12.16% and crashes (e.g., bike crash) by 62.74%. The underlying mechanisms are consistent with increased hedonic and tourist activities. Importantly, the effects are heterogeneous by the age and racial composition of a neighborhood; the benefits of e-scooters are attenuated and their downsides are aggravated in neighborhoods with relatively higher older population and people of color, revealing important asymmetries in the impact of e-scooters. Our research offers key implications and includes a research *app companion* for consumers, firms, and policymakers.

Keywords:
E-scooter, Shared Mobility, Retailing, Consumer Safety, Inequity, Difference-in-differences, Quasi-experiment

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INTRODUCTION

Shared micromobility services have grown rapidly in recent years. Globally, this industry is posited to surpass \$198.03 billion by 2030 (Precedence 2022). Within micromobility services, electric scooters (e-scooters, e.g., Bird, Lime, and Lyft) have grown in usage (Caspi, Smart, and Noland 2020; Oeschger, Carroll, and Caulfield 2020). The number of e-scooter trips increased from 38.5 million in 2018 to 86 million in 2019 (NACTO 2022). By 2019, e-scooters accounted for the largest share of shared micromobility trips and constituted what has been called the "scooter explosion" (Bloomberg 2020). By 2023, 156 cities in the United States (U.S.) have adopted e-scooters compared with 87 cities in 2019 (BTS 2023). Cities primarily introduce e-scooters to improve equitable access to mobility and to reduce emissions. However, several cities have also banned or restricted e-scooters due to their safety concerns, e.g., Atlanta banned e-scooters at night after four riders were killed (Short 2019), Paris banned e-scooters due to safety concerns (Mossalgue 2022), and London faced an e-scooter crime wave of hit-and-runs and drive-by shootings (Boyle 2021).

Despite the rising popularity of e-scooters and mixed expectations among cities regarding their economic and social impact, there is little empirical understanding about how they affect consumers, firms, and society (Mays 2023). Research in marketing has mainly examined the effect of e-scooters on restaurant visits and spending but the effects beyond the restaurant industry are less clear (Kim and Kannan 2023; Kim and McCarthy 2023). Furthermore, many cities introduce e-scooters with the objective of enhancing equity; the city of Chicago requires e-scooters to enhance "access and opportunities for groups who have the greatest need" (Brown, Howell, and Creger 2022). However, we do not know much about how e-scooters impact various social groups in a city based on their age, race, and socio-economic status.[1]

Our research has three objectives. First, we examine how the entry of e-scooters in a city impacts important economic and societal outcomes, including other shared mobility

[1] Cities define equity mainly based on demographics, e.g., San Francisco views e-scooters as "transforming systems to support the collective liberation of Black, Indigenous, and People of Color" (Brown, Howell, and Creger 2022).

(i.e., rideshare and bikeshare trips), retail visits (i.e., visits to restaurant and retail stores), and consumer safety (i.e., crimes and crashes). Second, we examine whether the impact of e-scooters varies by the type of neighborhood based on the age and racial composition of its residents (i.e., for older populations and people of color) in order to understand the heterogeneous impact of e-scooters. Such an inquiry allows us to better evaluate whether the introduction of e-scooters by a city is successful in achieving its equity goals. Finally, we descriptively explore the underlying mechanisms behind the effects.

To answer our research questions, we leverage a quasi-experiment using the geo-fenced entry of e-scooters in parts of Chicago in June 2019. We assemble a unique dataset over the 41-week period between January and October 2019, combining census-tract level data on shared mobility trips and consumer safety from the City of Chicago Data Portal, retail visits at the store level from SafeGraph, and demographic data from the U.S. Census Bureau. We first verify that the areas in which e-scooters were allowed did not differ from the areas in which e-scooters were not allowed (i.e., non e-scooter area) by the city of Chicago in terms of the demographics and pre-entry trends to ensure a valid comparison. We use a difference-in-differences (DID) approach that compares the change in outcomes in the e-scooter area with those outside the e-scooter area before and after the entry of e-scooters. We also report the results for alternative identification strategies, including a propensity score matching (PSM) analysis and a border discontinuity analysis to address potential selection concerns (e.g., Bekkerman et al. 2022; Goli, Mummalaneni, and Chintagunta 2023).

The results from our analysis of the effect of e-scooters reveal several interesting insights. First, we find that the entry of e-scooters increases the number of short rideshare trips by 3.01% but decreases the number of bikeshare trips by 24.98%; this finding reveals that e-scooters are complementary to ridesharing but cannibalize other micromobility options, such as bikesharing. Second, we find that the entry of e-scooters increases retail visits both to restaurants and other retail stores. Specifically, visits to restaurants increase by 1.77% and visits to other retail stores increase by 8.37%. Third, our results on consumer safety show that the entry of e-scooters increases crimes (e.g., vehicle break-ins) by 12.16% and crashes (e.g., bike accidents) by 62.74%. Our research shows that e-scooters have a dual impact of improving economic activity while adversely affecting societal outcomes, such as crimes and crashes in a city. Importantly, the results from our heterogeneity analysis show that the benefits of e-scooters are attenuated and their downsides are aggravated for areas with relatively older populations (i.e., above the median age of 34 years) and people of color (POC, i.e., majority non-white population). Specifically, we find that the increase in retail visits is less positive for such populations. We also find a more positive effect on crashes and a less positive effect on the number of rideshare trips in areas with a higher proportion of POC. Overall, our research reveals the dual and asymmetric impact of e-scooters on economic and societal outcomes for various populations. Our exploration of the potential mechanisms suggests that e-scooters may be increasing hedonic consumption (e.g., more visits to bars and drinking places) and attracting more tourism (e.g., higher hotel and home-rental demand), which help explain the overall pattern of results.

Our research contributes to the prior literature on sharing economy and micromobility, and the research on marketing for social and environmental good. First, most extant research on the sharing economy focuses on home- and ride-sharing platforms, such as Airbnb and Uber (e.g., Barron, Kung, and Proserpio 2021; Zervas, Proserpio, and Byers 2017). This literature mainly captures the effects of sharing economy platforms on the same industry albeit with a few recent exceptions (e.g., Shin et al. 2023 quantify the impact of Uber on restaurant quality through labor market changes and Zhang et al. 2022 quantify the effect of ridesharing on home-sharing). In contrast, we examine the effect of the entry of a shared micromobility innovation (i.e., e-scooters) on other shared mobility, retailing, and consumer safety. Second, to our knowledge, there is only one other paper on e-scooters in marketing but it focuses on the effects of e-scooters across cities and mainly on the food sector (Kim and McCarthy 2023). Prior research in marketing has not examined the impact of the entry of e-scooters on other key outcomes, such as other shared mobility, retail visits, and consumer safety. It is important for cities and policymakers to understand the broader economic and societal effects of e-scooters (Asensio et al. 2022). Prior research has also not explored the effects *within* a city. Most cities launch e-scooters in some areas so a *within-city* analysis is critical. Finally, while marketing research has examined race, age, gender, and other sources of bias in many settings like auto loans, personal care products, and digital platforms (e.g., Ozturk, He, and Chintagunta 2023; Moshary, Tuchman, and Vajravelu 2023; Zhang et al. 2021), we do not know how micromobility interventions, such as e-scooters impact minority populations that are often the intended beneficiaries of micromobility programs. We uncover the heterogeneity in the effects of the entry of e-scooters by the composition of residents; our insights add to the emerging research on diversity, equity, and inclusion by quantifying the impact of e-scooters for neighborhoods with a higher proportion of relatively older populations and POC.

Our research has several implications for stakeholders, including shared mobility platforms, retailers, and policymakers. First, our results on the complementarity and substitution between e-scooters and other forms of shared mobility can guide mobility platforms (e.g., Uber, Divvy) in their service placement and customer engagement efforts in response to the introduction of e-scooters in a city. Second, our results on increased retail visits suggest an opportunity for retailers to partner with e-scooter companies, e.g., to send targeted notifications to users through e-scooter apps when a ride is detected near their store. Third, policymakers can draw insights from our findings for the deployment and regulation of shared mobility services. Given the asymmetric impact of e-scooters for older populations and POC, policies can be better directed at equitable access and incentivized in neighborhoods with more minority populations. Finally, our research highlights ways in which e-scooter rollouts may fall short of accomplishing their broader goals of reducing car use via ridesharing and of enhancing overall equity.

Our research accompanies a specialized and novel interactive research app with at least four key benefits. First, the app extends the contribution of the research by providing an interactive interface for managers, researchers, and policymakers to visualize the results from our research and gain additional insights. Second, it allows stakeholders to view custom reports relevant to them by selecting their main function (e.g., Uber/Lyft driver, Department of Transportation employee, retailer). Third, the app documents additional analyses for a new set of variables (e.g., speed violations, taxi service) not focal to the paper, thus expanding the paper's scope without detracting from its narrative. Finally, leveraging the power of geo-location data, the app serves as a visualization tool to generate heatmaps and explore patterns in the data for generating new research questions. As an *explorer* app, it provides a user-friendly template and can be easily expanded to other cities with similar data as well. We provide the details of the app's contribution in the Section App Implementation.

RELATED LITERATURE AND CONCEPTUAL DEVELOPMENT

Our conceptual foundation is based on two distinct streams of research, i.e., the research on sharing economy and on marketing for social and environmental good. In this section, we first review the relevant literature in these two streams of research. Based on the collective insights from this work, we then lay out our expectations about the impact of e-scooters on shared mobility, retailing, and consumer safety. We develop expectations on how e-scooters may impact different types of neighborhoods based on two important sources of heterogeneity, i.e., the age and racial composition of a neighborhood.

Prior Literature: Key Insights and Limitations

Sharing Economy and Micromobility. Our research relates to the literature on sharing economy, particularly shared micromobility services. Most extant literature on sharing economy platforms has examined the economic effects of home-sharing (e.g., Airbnb) and ridesharing (e.g., Uber) platforms (e.g., Cramer and Krueger 2016; Dowling, Manchanda, and Spann 2021; Eckhardt et al. 2019). The findings from this literature show that the entry of Airbnb impacts the housing and hotel industries (Barron, Kung, and Proserpio

2021; Zervas, Proserpio, and Byers 2017); it decreases hotel revenues (Zervas, Proserpio, and Byers 2017), impacts hotel pricing (Li and Srinivasan 2019), increases house prices and rents (Barron, Kung, and Proserpio 2021), boosts residential real estate investment (Bekkerman et al. 2022), and cannibalizes long-term rental supply (Li, Kim, and Srinivasan 2022). A few recent studies have focused on the broader implications of sharing economy platforms for society and how they contribute to socio-economic and racial inequality (e.g., Fu et al. 2023; Zhang et al. 2021). Collectively, the sharing economy research mainly quantifies the economic effect of sharing economy platforms within the same or a closely related industry. One exception is a recent study by Shin et al. (2023) that quantifies the impact of ridesharing on the restaurant industry (i.e., restaurant quality) through labor market changes and shows that ridesharing platforms lower the quality of service at restaurants by raising their staff turnover. Similarly, Zhang et al. (2022) quantify the effect of ridesharing on home-sharing. In contrast, we focus on the effect of the entry of shared e-scooters on both economic and societal outcomes.

Based on our review, the sharing economy literature seldom focuses on micromobility services. Two recent studies relating to e-scooters and bike sharing platforms come closest to our research (Chu et al. 2020; Kim and McCarthy 2023). Chu et al. (2020) show that the entry of bikesharing platforms Ofo and Mobike in ten cities in China improved connectivity between homes and subway stations, attenuating price premiums for housing. Kim and McCarthy (2023) show that cities with e-scooter entries tend to attract more spending at restaurants than cities without e-scooters across multiple cities in the U.S. that launched e-scooter programs in 2018, quantifying their impact on the food sector. Our research differs from and is complementary to Kim and McCarthy (2023) in at least three ways. First, we examine the broader impact of e-scooters on both economic and societal outcomes, including other shared mobility, retailing, and consumer safety. It is important to quantify the impact of e-scooters on consumers and firms beyond the food industry to help cities and policymakers better evaluate and regulate them. Second, we examine the effects of the entry of e-scooters *within* a city using data on select locations in which e-scooters were made available. Micromobility regulations tend to be city-specific, e.g., allowing e-scooters in certain parts of a city, so the within-city analysis is useful for both policy and local business decisions (e.g., Mays 2023; Nield 2022; Toll 2023). Finally, we examine the heterogeneity in the effects of e-scooters based on the age and racial composition of a neighborhood, revealing important asymmetries for relatively older populations and POC. Such an inquiry provides insights and implications for access and equity, which are important goals of shared micromobility programs in most cities (Brown, Howell, and Creger 2022).

Overall, the sharing economy literature predominantly evaluates the effect of the entry of a shared platform on the same or similar industries and seldom focuses on micromobility services or their socio-economic impact. Our research quantifies how the entry of e-scooters impacts other shared mobility, retailing, and consumer safety *within* a city, suggesting important asymmetries by the type of neighborhood.

Marketing for Social and Environmental Good. Our research relates to the literature on marketing's impact on society (e.g., Chandy et al. 2021; Kelly 1971; Kotler and Lee 2008). In recent years, there has been a greater call for examining and measuring marketing's broader impact (Hanssens and Pauwels 2016), including how marketing impacts consumer wellbeing, health, and safety (e.g., Berry et al. 2020; Chen et al. 2023; Seiler, Tuchman, and Yao 2021) and a concern for sustainability (e.g., Gonzalez-Arcos et al. 2021; Varadarajan 2017). Introduction of environmentally-sustainable products by brands generally improves brand attitudes (Olsen, Slotegraaf, and Chandukala 2014). However, environmental innovations can also backfire due to consumer resistance (e.g., Gonzalez-Arcos et al. 2021; Zhang, Chintagunta, and Kalwani 2021). Many marketing interventions create both positive and negative externalities, e.g., the flipside of new technologies is self-control issues and a tendency among users to shop around (Allcott, Gentzkow, and Song 2022; Gu and Kannan 2021). Therefore, it is important to capture the overall impact of new technologies.

Recent research in marketing has also documented how the benefits and costs of marketing efforts get distributed among various subgroups of consumers, particularly minorities. Digital platforms' strategies, for example, are shown to result in unintended and inequitable effects for various groups. Zhang et al. (2021) show that the overall earnings gap between Black and White hosts increased due to Airbnb's smart-pricing algorithm because of low adoption rates among Black hosts. Similarly, Zhu, Shi, and Banerjee (2023) demonstrate the inequitable effect of a platform monetization strategy on *Goodreads.com* that increased the market share of major and established participants at the expense of smaller entities with fewer resources.

Most prior research examining diversity, equity, and inclusion (DEI) concerns in marketing has focused on either documenting bias and discrimination in different industries (e.g., Karniouchina et al. 2023; Scott et al. 2023) or on how pricing policies differentially affect minority groups (e.g., Moshary, Tuchman, and Vajravelu 2023; Ozturk, He, and Chintagunta 2023, Wang et al. 2022, Zhang et al. 2021). Karniouchina et al. (2023) and Scott et al. (2023) document gender- and race-related disparities in the movie industry and racial bias in the financial loan services respectively. Research also offers evidence evaluating price disparity for minorities. In case of personal care products, Moshary, Tuchman, and Vajravelu (2023) reveal that over 80% of products sold are gendered but that there is no evidence of a systematic price premium for women's goods. Ozturk, He, and Chintagunta (2023) show that women and minorities are subject to 0.6%-2.6% higher interest rate markups on auto loans than men and non-minorities, and that premia are larger in census tracts with lower education levels. In the auto repair shop pricing, Busse, Israeli, and Zettelmeyer (2017) show that women are quoted higher prices than men when callers signal that they do not have price information. Other survey-based approaches also show that older people are more likely to be victims of investment fraud (Deliema, Shadel, and Pak 2020). In the restaurant industry, Aneja, Luca, and Reshef (2023) find that labeling restaurants as "Black-owned" on an online platform increases online traffic, calls, orders, and visits to the restaurant. Collectively, emerging research in marketing has documented how marketing impacts people of color, older populations, women, and other sub-groups in various industries.

Complementary to this body of work, our research examines the heterogeneity in the effects of the entry of e-scooters in terms of the age and racial composition of neighborhoods. As a new form of micromobility, e-scooters are deployed within a city to increase consumers' equitable access to mobility options, particularly for those who were "historically excluded" (Brown, Howell, and Creger 2022). Our research uniquely examines how the effects of e-scooters on economic and societal outcomes vary by residents' age and race profiles. Such an inquiry is important because the cost of poor infrastructure (e.g., roads) often falls unevenly on predominantly Black neighborhoods (Currier, Glaeser, and Kreindler 2023).

Expected Effects of E-scooter Introduction

Based on our review of the literature, we next lay out our expectations for the effects of e-scooters on our key outcomes of other shared mobility, retailing, and consumer safety.

Other shared mobility. E-scooters provide an alternative mobility option to consumers. They exhibit several distinct capabilities that make them appealing. First, e-scooters solve the last-mile problem by providing direct access to pick-up and drop-off points by virtue of being dockless, unlike public transportation and docked bikes (Baek et al. 2021). Second, e-scooters are faster for completing short trips compared with walking, biking, and even ridesharing in case of adverse traffic and terrain (Asensio et al. 2022). Finally, e-scooters offer an enjoyable experience due to their novelty and thrill.

Based on the unique and distinct features of e-scooters, we next discuss their potential effects on other forms of shared mobility (i.e., ride and bike sharing). On one hand, after the entry of e-scooters, it is possible that consumers will continue to use pre-existing bikesharing options as they offer a low-cost option consumers are already used to (NACTO 2022). It is also likely that some consumers will supplement their docked bike trips with e-scooters for last-mile access to the bike station. On the other hand, it is also possible that e-scooters will replace bikesharing trips because they are faster, more convenient for pick-up and drop-off anywhere, and do not require much physical effort. Therefore, e-scooters could replace shared bike trips particularly for populations that are either unable to or do not wish to exert the effort required for propulsion in case of bikes (Yang et al. 2021).

Similarly, at least short ridesharing trips may be substituted by e-scooters. One of the main motivations for introducing e-scooters is to reduce car usage, including car ridesharing services (Asensio et al. 2022). A substitution effect on ridesharing will likely show that e-scooters were successful in their initial goals, and may also contribute towards improved environment through reduced carbon emissions (Guo and Zhang 2021). However, it is also possible that e-scooters will serve a complementary relationship with ridesharing, for example, if e-scooters are used in conjunction with ridesharing (e.g., consumers may use an e-scooter to go to a bar on Friday night, but then take an Uber to go home).

Overall, based on these arguments, we expect that e-scooters will decrease bikeshare trips but may increase rideshare trips due to their overlapping (vs. distinct) capabilities.

Retailing. We expect e-scooters to have a positive effect on the visits to restaurants and retail stores, consistent with extant research. Research shows that the introduction of e-scooters in cities increases consumer spending at restaurants, and in particular, for hedonic food options like fast-food joints (Kim and McCarthy 2023). Research also shows that commuting behaviors impact consumers' purchases and consumption (Andrews et al. 2015; Ghose et al. 2019; Ghose, Li, and Liu 2019). Commuters are three times more likely to redeem food-related marketing coupons relative to non-commuters due to psychological and physiological factors (Ghose et al. 2019). Commuters in a crowded subway train are twice as likely to make a purchase than those in a noncrowded subway train since being in a crowded train makes them focus inwards (Andrews et al. 2015). Because commuting impacts consumers' purchases by altering their state of mind and e-scooters provide consumers a novel and thrilling experience, we expect e-scooters to increase consumers' restaurant visits, particularly for hedonic food categories.

Over 30% e-scooters users report fun and leisure as their main purpose of using e-scooters (Keane 2022). E-scooters can put users in an inspired and exploratory mindset rather than a goal-oriented mindset and increase their unplanned shopping visits (Grewal et al. 2023). Therefore, it is likely that e-scooters will increase the visits to retail stores (e.g., department stores for shopping) and will likely attract spontaneous visits (Zhang et al. 2022). Tourists, for instance, might find e-scooters an attractive option for a more immersive exploration of local cuisines and shopping districts, thereby enhancing the foot traffic in these places. Similarly, e-scooters may boost hedonic consumption by virtue of being an enjoyable and pleasurable experience (Janiszewski 1998). However, we only expect this effect for large department stores that promote a shoping experience and not for grocery chains, which tend to be a functional shopping category.

Overall, based on these arguments, we expect e-scooters will lead to increased consumer visits to restaurants and retail stores by encouraging a more exploratory mindset.

Consumer Safety. E-scooters, although potentially helpful for consumer mobility and retailing, can also create a public nuisance by blocking sidewalks, threatening pedestrian and passenger safety, and increasing crimes (e.g., Pham 2021; Sanders, Branion-Calles, and Nelson 2020). The marketing literature considers various types of consumer safety following Maslow's Need Hierarchy; Berry et al. (2020) characterize consumer safety in services from the lens of physical safety (i.e., absence of injury), emotional safety (i.e., relief from mental distress), financial safety (i.e., minimizing economic insecurity), and information safety (i.e., access to the right information). Physical safety, though at the base of Maslow's need hierarchy, is an important priority for marketers (Chen et al. 2023). Given the high speeds of e-scooters and lack of adequate infrastructure (e.g., scooter lanes and parking) in most cities, it is likely that e-scooters will increase the risk of accidents and injuries (Chattopadhyay 2021). Similarly, it is possible that they will result in a higher incidence of street crimes (e.g., snatch wallets or cash, break into a parked car) as they allow a quick escape from the site of crime (Charles 2023). Many cities report theft of e-scooters themselves as a crime (Coredero 2022). On the flipside, since e-scooters aim to enhance mobility, improve commute speeds, and reduce wait times, they could also expand employment opportunities (Lam, Liu, and Hui 2021). E-scooters, if successful in providing accessible and affordable commute options to low socio-economic populations, could improve economic status and potentially even reduce the incidence of crime in the long-term.

Overall, based on these arguments, we expect that e-scooters will worsen consumer safety by increasing the number of crimes and crashes in a city.

Expected Heterogeneity in Effects. The main effects of the entry of e-scooters on other shared mobility, retailing, and consumer safety could vary depending on the type of neighborhood based on the age and racial composition of its residents. Based on prior DEI literature, minority populations are less likely to adopt and take advantage of new innovations like e-scooters (e.g., Wilson 2020). Furthermore, relatively older people may be less likely to use e-scooters due to their speed and potential risk of injury compared to using a car or other traditional forms of transportation. POC may be hesitant to be exposed during e-scooter ride particularly in light of recent anti-black violence (e.g., Moss 2023; Wilson 2020). It is also possible that conditional on usage, older populations and POC will likely benefit less from the use of e-scooters (Currier, Glaeser, and Kreindler 2023). For example, relatively lower socio-economic conditions in their neighborhoods could prevent them from taking full advantage of the improved economic activity (e.g., more retail visits) that results from the entry of e-scooters (Frias-Martinez et al. 2021). Overall, we posit that the benefits of e-scooters will likely be less favorable while their costs may be exacerbated in neighborhoods with a higher proportion of relatively older populations and POC.

RESEARCH SETTING AND DATA

Research Setting

The City of Chicago launched a shared e-scooter program on June 15, 2019. Ten e-scooter companies were allowed to operate within a 50-square mile area in Chicago. These companies were Bird, Bolt, Grüv, JUMP, Lime, Lyft, Sherpa, Spin, VeoRide, and Wheels. The e-scooter area included neighborhoods with diverse populations (e.g., areas with both White and non-White populations) and residential characteristics (e.g., both residential and commercial areas). The city ensured the availability of e-scooters throughout the e-scooter area and a geofencing technology prohibited e-scooters from leaving the defined area.

The entry of e-scooters in Chicago offers a quasi-experimental setting to examine the impact of the entry of e-scooters on economic and societal outcomes. Using the e-scooter boundary defined by the city, we treat census tracts in the e-scooter area as the treatment group (i.e., exposed to e-scooters) and census tracts outside the e-scooter area as the control group (i.e., not exposed to e-scooters). The use of census tracts allows us to observe heterogeneity in the demographics of the neighborhoods in our data at a more granular level than zip codes (e.g., Ozturk, He, and Chintagunta 2023). We then compare the economic and societal outcomes in the treated and control areas before and after the entry of e-scooters to quantify the effects on our outcomes of interest (i.e., shared mobility, retail visits, and consumer safety). Our identification strategy is described in the Section Empirical Strategy.

Data Description

Our data span January to October 2019 and 866 census tracts in Chicago. The e-scooter data from the City of Chicago Data Portal provides us with information about the locational coordinates of the geographical region in which e-scooters were allowed to enter and operate within Chicago. We use these data to identify the treated and control regions inside and outside the e-scooter boundary. We observe data over 23 weeks in the pre-entry period and 18 weeks in the post-entry period.

In addition to the data on the e-scooter boundary, we collect data from five different sources. First, we collect trip-level data on rideshare and bikeshare services from the City of Chicago Data Portal. We also collect the crime and crash records from this portal. These data include the geolocation and datetime stamps for each record. Second, we collect retail store-level visit data from Safegraph, a company that records the global positioning system (GPS) data based on mobile pings at various locations visited by consumers. Third, we collect census tract-level demographic data for each census tract in our data. Fourth, we collect Airbnb listing data from the Inside Airbnb website. Finally, we obtain restaurant category data from Yelp for analyzing the potential mechanisms. In this section, we describe these various datasets starting with the data on our main outcome variables and then the data used for additional heterogeneity and mechanism analyses.

Our focal dependent variables are other shared mobility (i.e., rideshare and bikeshare trips), retail visits (i.e., visits to restaurants and retail stores), and consumer safety (i.e., crimes and crashes). *Rideshare* and *Bikeshare* refer to the weekly number of trips made using rideshare (e.g., Uber) and bikeshare (e.g., Divvy) services. To compute the number of trips, we aggregate trips starting in each census tract based on the longitude and latitude coordinates of the trip and of the census tract. We have data on over 38 million trips in 697 census tracts for ridesharing and 0.75 million trips in 231 census tracts for bikesharing.[2]

Retail visits to *Restaurants* and *Retail stores* refer to the weekly number of visits to retailers categorized as restaurants or other retail stores. We use the SafeGraph data to compute the number of visits each week to each retail store for a subset of the U.S. population represented in these data.[3] The Safegraph data also have a unique identifier, location information, and geometric polygons of each store. These data allow us to identify whether a retail store is located in the e-scooter area or not. We have data on 3,915 restaurants and 3,172 retail stores that are located in the census tracts in our data. An illustrative list of businesses included in our data appears in Web Appendix Table A.1.

The number of *Crimes* represents the weekly number of street and vehicle-related crimes at the census tract level. The number of *Crashes* represents accidents involving bikes or scooters at the census-tract level. The data on crimes and crashes include geolocation information (i.e., longitude and latitude) which allow us to identify the census tract in which the crime and/or crash occurred. In our data period, 734 and 684 census tracts had

[2]Note that in the main analysis, we focus on short ridesharing trips of under two miles that are relevant to e-scooters. However, in Web Appendix Table E.2, we also report the results for long trips.

[3]SafeGraph aggregates data from 45 million smartphone users. These data accurately identify 95% of a brand's actual locations when compared to first-party data from that brand and other public data sources (Kendall 2021).

at least one incident of such crime and crash respectively.

Next, we collect demographic information at the census tract level from the U.S. Census Bureau. The demographic data include the total population, young population (i.e., under the median age of 34 years old), number of people classified as non-white or POC, and mean household income in each census tract in Chicago.

In addition to the data on our key outcomes and demographics, we also collect data for additional mechanisms analysis. We use data on restaurant characteristics from Yelp. Specifically, we extract information on the detailed category tags for each restaurant. For example, Pizza Hut is tagged as "pizza" and "fast food." We assign restaurants to one of 10 main categories based on this tag information (see Web Appendix Table B.1), namely, American, Asian, Bar, Burger, Coffee, Dessert, European, Latin American, Pizza, and Sandwiches (consistent with Klopack 2022). Finally, we also collect Airbnb listing data on listing-level availability from the Inside Airbnb website and the data on visits to tourist sites, such as museums from SafeGraph.

Summary Statistics

The summary statistics for our data appear in Table 1. On average, there are 392 rideshare trips and 74 bikeshare trips in a census tract in a week during our data period. We also observe 6.74 visits to restaurants and 6.08 visits to other retail stores on average from our sample customers in the Safegraph data. Finally, there are 1.31 crimes and 0.06 crashes in a week in a census tract in our data period.

As reported in Table 1, the average population in a census tract is 3,469.00 and the average number of young population below the age of 34 years is 1,763.00. The average number of POC is 1,753.70 in a census tract. The average household income is $65,208.00 per annum. Finally, the data on e-scooter trips show that an average e-scooter trip is 1.51 miles in distance.

Table 1: Variable Description and Summary Statistics

Variable	Description	Mean	Std Dev
Other shared mobility			
Rideshare	Weekly number of short rideshare trips of under two miles at the census tract level	392.10	1525.21
Bikeshare	Weekly number of bideshare trips at the census tract level	73.9	137.26
Retail visits			
Restaurant	Weekly number of visits to retailers categorized as restaurant	6.74	13.65
Retail store	Weekly number of visits to retailers categorized as shopping	6.08	12.93
Consumer safety			
Crime	Weekly number of street and vehicle-related crimes at the census tract level	1.31	1.73
Crash	Weekly number of bike and scooter crashes at the census tract level	0.06	0.26
E-Scooter	Dummy = 1 if in e-scooter area, 0 if in control area	0.36	0.48
Post entry	Dummy = 1 if after the entry of e-scooters, 0 if not	0.44	0.50
Population	Total population in census tract	3,469.00	1,761.18
Young population	Total population below 34 years old in census tract	1,763.00	950.94
POC	Total population of people of color	1,753.70	1,487.89
Income	Annual household income ($) in census tract	65,208.00	36,951.91
Trip distance	Average distance of an e-scooter trip (miles)	1.51	1.66

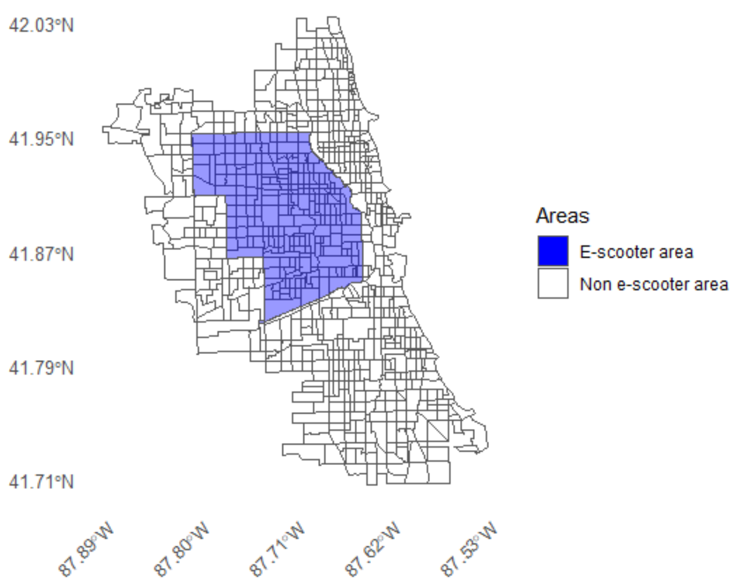
Notes: The summary statistics of retail visits are computed at the retailer-week level in the weeks before and after the entry of e-scooters; the other outcome variables are at the census tract-week level before and after the entry of e-scooters. POC = People of color.

EMPIRICAL STRATEGY

Our overarching goal is to examine how e-scooters impact a rich set of economic and societal outcomes, including other shared mobility (i.e., rideshare and bikeshare), retail visits (i.e., restaurant and retail stores), and consumer safety (i.e., crimes and crash). To do this, we use a DID approach (Angrist and Pischke 2009) to compare the change in the outcome variables in the e-scooter area with the change in the outcome variables in the non e-scooter area before and after the entry of e-scooters.

We identify the e-scooter area as the 50-square mile area located in the city of Chicago where e-scooters were allowed to operate in 2019 using the polygons provided by the City of Chicago Data Portal. We consider all the census tracts in this region as the e-scooter area (i.e., treated). To identify the non e-scooter area (i.e., control), we include census tracts outside this area but within 10 miles of the e-scooter boundary (e.g., Goli, Mummalaneni, and Chintagunta 2023).[4] Figure 1 shows a map of the treatment and control regions.

Figure 1: E-scooter Area in Chicago

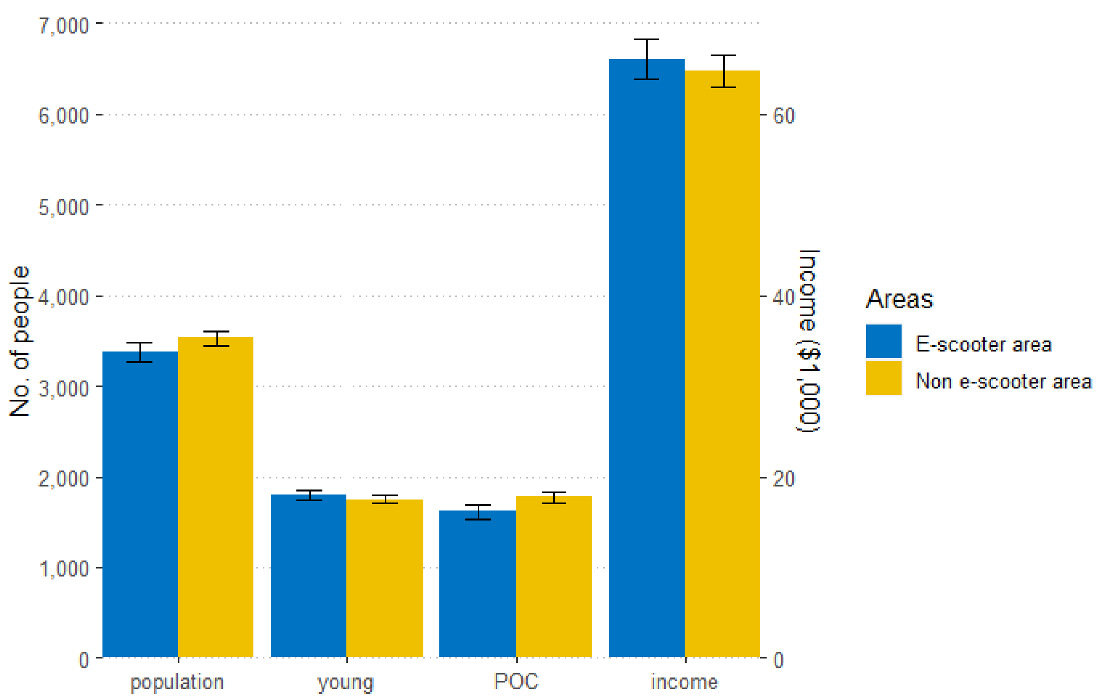


[4]We chose the 10-mile distance based on maximum distance of e-scooter trips. The results are consistent for alternative distance thresholds closer to the e-scooter boundary. See Section Border Discontinuity Analysis. We exclude the Chicago airport and forest preserve as these areas are idiosyncratic in their population and farther away.

To verify that we have a valid control group comparable to the treatment group, Figure 2 reports the demographic characteristics of the census tracts in the treatment and control areas. This figure shows that the e-scooter and non e-scooter areas have similar demographic characteristics in terms of their population, young population, POC, and income.

For the DID approach to be valid, the change in the outcome variables in the non e-scooter area should be a good counterfactual for the change in the outcome variables in the e-scooter area before and after the entry of e-scooters. We visually inspect the trends of the outcome variables in both e-scooter and non e-scooter areas before the entry of e-scooters. Web Appendix Figures C.1 - C.6 report these trends of the six outcome variables between the treatment and control groups. The pre-period trends of the six outcome variables in the e-scooter and non e-scooter areas appear similar.

Figure 2: Comparison of Demographic Characteristics between the Treatment and Control Areas



Notes: Population is the number of inhabitants; young population is the number of inhabitants under 34 years old; POC is the number of inhabitants of people of color. E-scooter area (i.e., treatment group) denotes the area in which e-scooters were allowed; non e-scooter area (i.e., control group) denotes the area in which e-scooters were not allowed.

Difference-in-differences Model with Two-Way Fixed Effects

To quantify the effect of the entry of e-scooters, we estimate the following difference-in-differences model with two-way fixed effects:

$$Y_{it} = \alpha_0 + \alpha_1 \textit{E-Scooter}_i \times \textit{PostEntry}_t + \tau_t + \vartheta_i + \epsilon_{it} \tag{1}$$

Where Y_{it} refers to the outcome variable Y in the week t for a location i. The location i refers to the restaurant or retail store in case of retail visits and to the census tract in case of other outcomes due to the nature of data available. *E-Scooter* is a dummy variable denoting the entry of e-scooters (1 if the location i is inside the e-scooter area and 0 otherwise), *PostEntry* is a dummy variable denoting the period (1 for the period after the entry of e-scooters and 0 otherwise), α is a coefficient vector, τ indicates the week fixed effects, ϑ represents the location (i.e., census tract or retailer) fixed effects, and ε is an error term. The coefficient of *E-Scooter* $\times$ *PostEntry*, i.e., α_1, identifies the effect of the entry of e-scooters. The identifying assumption is that the average weekly change in the outcome variables in the control group is a valid counterfactual for the change in the outcome variables in the treatment group before and after the entry of e-scooters.

The DID model with two-way fixed effects is particularly suited for our panel data structure, which comprises observations across different census tracts or retail stores over time (De Chaisemartin and d'Haultfoeuille 2020). It quantifies the impact of the entry of e-scooters on the outcome variables, isolating the effect from both time-invariant unit characteristics (i.e., census tract and retail store) and common time effects. Therefore, this model helps address potential confounding factors. Although we verified the assumptions of this approach in our setting i.e., the observed characteristics and pre-treatment trends in the treatment and control groups are similar, we also employ propensity score matching and border discontinuity designs to mitigate potential selection concerns.

Endogeneity and Self-selection

The entry of e-scooters represents an exogenous shock in cities where e-scooters are allowed to operate. Most cities launch e-scooters with the objective of reducing traffic and carbon emissions rather than promoting other outcomes like retail and safety (NACTO 2022). It is unlikely then that cities will selectively launch e-scooter programs only in areas with higher economic or social activity (Kim and McCarthy 2023). In case of Chicago, the quasi-experimental setting in our research, we do not find evidence of strategic deployment of e-scooters in areas with systematically high or low economic and social activity. Nonetheless, we conducted several checks and robustness analyses to verify the validity of our estimates.

First, we verified that the e-scooter area designated by Chicago was similar to the non e-scooter area in terms of demographics (see Figure 2). Second, we verified that the pre-period trends for our outcome variables are parallel (see Web Appendix Figures C.1 - C.6). We also report the treatment effects for the pre-entry weeks in Web Appendix Table C.7 as a test of parallel trends. Third, we descriptively examine the possibility that within the city of Chicago, e-scooters could have been deployed more in areas with a higher or growing micromobility demand but we did not find any evidence for this; the average number and trend of bikeshare trips in both treatment and control areas in the pre period are similar ($p > 0.10$). Fourth, it is possible that e-scooters are launched in higher population areas, which could be correlated with higher shared mobility, retail demand, and safety concerns. We examined correlations between the entry of e-scooters and the demographics of a census tract (e.g., population, income) and find each of them to be low, i.e., under 0.20. Finally, in this institutional setting, it is also less likely that retailers (i.e., restaurants and retail stores) will self-select to locate in areas with e-scooters since retail location is a long-term decision. We also verified that the retailers in our data existed prior to the entry of the e-scooters and as such, they could also not have pre-empted the timing or locations of e-scooter entry (Ergin, Gümüş, and Yang 2022). We verified that the entry of e-scooters could not be pre-empted in advance by other stakeholders; it was not announced until close to the rollout in May.

Although the parallel trends in pre-treatment outcomes and our additional checks provide us with reasonable confidence in our empirical approach, we also combine the two-way fixed effects model with a PSM approach commonly used in quasi-experimental marketing research (Goldfarb, Tucker, and Wang 2022). The idea is to use observed census tract characteristics and past levels of each outcome in the pre-entry period to construct a control group that matches the treated group, and provides valid counterfactual comparisons.

First, we model the probability of a census tract (or retailer in case of retail visits) being in the e-scooter area or not as a function of observed characteristics, such as the past values of the outcome variable for the pre-entry period, population, young population, income, and POC in that area. Next, we calculate the propensity score for each of the six outcome variables using the following binomial logit model:

$$\widehat{p}_i = \Pr\left(Escooter_i = 1 \mid X_i\right) = \frac{\exp\left(\beta_0 + \beta_1 X_i\right)}{1 + \exp\left(\beta_0 + \beta_1 X_i\right)} \tag{2}$$

where $\widehat{p}$ is the propensity score, i is either a census tract or the retailer, $Escooter$ is the treatment i.e., the entry of e-scooters in that area, X is a vector of covariates, and β is a vector of coefficients. X includes the relevant covariates (e.g., the past values of the outcome variable for the pre-entry period, population, young population, income, POC population).

Finally, we match the census tracts and retailers for each outcome variable in the e-scooter and non e-scooter area based on the nearest neighbor matching by minimizing the difference in propensity scores:

$$C\left(\widehat{p}_k\right) = \min_j \left\|\widehat{p}_k - \widehat{p}_j\right\| \tag{3}$$

where $\widehat{p}$ is the propensity score, k refers to units in the e-scooter area, and j refers to units in the non e-scooter area. For each outcome variable, we repeat the matching process. We use the logarithmic transformation of population, young population, POC population, and income because the past values of the outcome variables are relatively smaller and logarithmic transformation can keep a similar scale and ensure the stability in estimation.

Despite our TWFE and matching procedures, one possible threat to causality could be the violation of the stable unit of treatment value assumption (SUTVA) if e-scooter entry in the treatment area shifts outcomes in the control area. Since e-scooters cannot cross the geo-fenced boundary, there is no direct spillover. However, in the Section Robustness Checks, we further test and find robust estimates after excluding areas close to the boundary where spillovers could be possible by pedestrians or bikers. We also report a border discontinuity analysis in case there are unobservable differences farther away from the boundary.

RESULTS

The results from the DID model are presented in Table 2. This Table shows that there is a significant increase in the number of weekly rideshare trips (α_1 = 28.580, p $<$ 0.01) in the e-scooter area relatively to those in the non e-scooter area after the entry of e-scooters. We also find a decrease in the number of weekly bikeshare trips (α_1 = -6.094, p $<$ 0.05). We find an increase in the number of weekly visits to both restaurants (α_1 = 0.124, p $<$ 0.01) and retail stores (α_1 = 0.103, p $<$ 0.01). However, we find an increase in the weekly number of crimes (α_1 = 0.148, p $<$ 0.01) and crashes (α_1 = 0.017, p $<$ 0.05). Overall, the results indicate that while the entry of e-scooters contributes positively to rideshare and retail visits, it also negatively affects bikeshare and increases crimes and crashes.

Next, we describe the results of our propensity score matching (PSM). The PSM models match the treated group in the e-scooter area to the control group in the non e-scooter area for our dependent variables. For shared mobility and consumer safety, we match the treated group and control group at the census tract level. For retail visits, we matched the treated group and control group at the retailer level. Web Appendix Tables C.1 - C.6 show the summary of balance for the treated and control groups before and after matching. These tables show that after matching, the observed covariates of two groups look very similar. Web Appendix Figures C.7 - C.12 show the distribution of propensity scores for the treated

Table 2: DID Model Results of the Entry of E-scooters

	Shared mobility		Retail visits		Consumer safety	
Variable	Rideshare	Bikeshare	Restaurant	Retail Store	Crime	Crash
E-Scooter × Post entry (DID)	28.580***	-6.094**	0.124***	0.103***	0.148***	0.017**
	(3.810)	(2.679)	(0.034)	(0.046)	(0.034)	(0.007)
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes
N	28,577	9,471	160,515	130,052	30,094	28,044
Adj. R^2	0.986	0.770	0.910	0.887	0.506	0.090

Notes: Robust standard errors clustered by census tract are in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. DID = Difference-in-Differences. FE = Fixed effects. N = No. of observations. Retail stores include retailers such as grocery, clothing stores, and department stores.

and control groups before and after matching. After matching, the distribution of propensity scores for the control group appears similar to that for the treatment group.

Table 3: DID Model Results with Propensity Score Matching

	Shared mobility		Retail visits		Consumer safety	
Variable	Rideshare	Bikeshare	Restaurant	Retail store	Crime	Crash
E-Scooter × Post entry (DID)	12.792***	-12.530**	0.100**	0.532***	0.161***	0.020**
	(2.506)	(5.019)	(0.035)	(0.106)	(0.039)	(0.009)
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes
N	21,566	6,150	153,258	81,590	20,418	15,785
Adj. R^2	0.967	0.801	0.913	0.879	0.516	0.085

Notes: Robust standard errors clustered by census tract are in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. DID = Difference-in-Differences. FE = Fixed effects. N = No. of observations.

Table 3 presents the DID model results for the matched sample for each of the outcome variables. These results are consistent with the main results in Table 2. Specifically, the analysis reveals a significant increase in the average weekly number of rideshare trips at the census tract level by 12.792 ($p < 0.01$), post the entry of e-scooters. In contrast, the average weekly number of bikeshare trips shows a decrease of 12.530 ($p < 0.05$). These effects translate to a 3.01% increase in rideshare trips and a 24.98% decrease in bikeshare trips compared to their pre-treatment levels in the non e-scooter area.

In case of retailing, the entry of e-scooters results in an increase in the average weekly visits to restaurants and retail stores by 0.100 ($p < 0.05$) and 0.532 ($p < 0.01$) respectively. These effects translate to a 1.77% increase in visits to restaurants and a 8.37% increase in visits to retail stores compared to their pre-treatment levels in the non e-scooter area.

Importantly, there is a significant decline in consumer safety, evidenced by increases in the average weekly number of crimes ($\alpha_1 = 0.161$, $p < 0.01$) and crashes ($\alpha_1 = 0.020$, $p < 0.05$) following the deployment of e-scooters. These effects translate to a 12.16% increase in the number of crimes and a 62.74% increase in the number of crashes compared to their pre-treatment levels in the non e-scooter area.

Heterogeneity by Age and Race

Our main analyses show that the entry of e-scooters positively impacts economic activity, but it adversely impacts consumer safety and other forms of micromobility (i.e., bikeshare). We next investigate the heterogeneity in the effect of e-scooters based on the age and racial composition of a neighborhood.[5]

We set the median age of 34 as a threshold to differentiate the relatively younger and older populations. We calculate the percentage of older population for each census tract and define the areas with a higher percentage of older people as *High Older* for the heterogeneity analysis. Similarly, we calculate the percentage of POC for each census tract and define the areas with higher than median percentage of POC as *High POC*.

To examine the heterogeneity in the effects, we re-estimate our main regression with

[5]We also report analysis by socio-economic status (i.e., income) in Web Appendix Table E.1. However, we do not include income and race in the same model due to collinearity concerns. We do not observe gender information to examine effects for females (vs. males).

additional covariates that capture the interactions between the DID treatment effect (i.e., *E-Scooter* x *Post*) and each of our two moderating variables of interest: *High older* and *High POC*. These variables denote neighborhoods with higher than median proportion of older population and of POC based on median splits (see Section Data Description for details). We also include the main effects and two-way interaction terms of the moderating variables to estimate the model. Table 4 reports the results.

Table 4: DID Model Results of the Entry of E-Scooters for Heterogeneity by Race and Age

	Shared mobility		Retail visits		Consumer safety	
Variable	Rideshare	Bikeshare	Restaurant	Retail store	Crime	Crash
DID	10.270*	15.138**	0.164***	1.180***	0.146**	-0.001
	5.635)	(6.652)	0.045)	(0.187)	(0.062)	(0.019)
DID × High Older	19.891***	-52.886***	-0.100	-0.521***	0.014	-0.001
	(4.643)	(8.493)	(0.082)	(0.201)	(0.078)	(0.019)
DID × High POC	-11.049**	8.155	-0.159**	-1.088***	0.017	0.048***
	(4.514)	(8.194)	(0.076)	(0.205)	(0.080)	(0.018)
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes
N	21,566	6,150	153,258	81,590	20,418	15,785
Adj. R^2	0.968	0.818	0.913	0.879	0.516	0.087

Notes: Robust standard errors clustered by census tract are in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. DID = Difference-in-Differences. FE = Fixed effects. N = No. of observations. We also include the main effects and two-way interaction terms of the moderating variables *High older* and *High POC* with each term but do not report them to save space. *Retail store* includes retailers such as grocery chains, convenience stores, and department stores.

The results in Table 4 indicate several interesting patterns. First, we find that the effects of the entry of e-scooters are more positive for rideshare trips (19.891, $p < 0.01$) and more negative for bikeshare trips (-52.886, $p < 0.01$) among neighborhoods with higher older populations than those with a younger population. We also find that the effects of the entry of e-scooters are less positive for rideshare trips (-11.049, $p < 0.05$) among neighborhoods with a higher proportion of POC. The interaction term for high POC and the treatment effect is not significant for the number of bikeshare trips.

Second, the effects of the entry of e-scooters on retail visits are also heterogeneous and generally less positive for neighborhoods with higher older and those with higher POC populations. Specifically, the effect on restaurant visits is less positive in neighborhoods with a higher older population (-0.159, $p < 0.05$). Similarly, the effect on the number of visits to retail stores is less positive in case of both higher older (-0.521, $p < 0.01$) and higher POC (-1.088, $p < 0.01$) neighborhoods. Overall, the positive effects of the entry of e-scooters on retail visits are negatively moderated by *High Older* and *POC*. These findings suggest that in neighborhoods with a higher proportion of relatively older people and of POC, the positive economic effects of e-scooters are relatively lower.

Third, we also find a significant interaction between the treatment effect and high POC neighborhoods for crashes. Specifically, the effect of e-scooters on crashes is more positive in neighborhoods with a higher proportion of POC (0.048, $p < 0.01$) indicating the worse societal impact of e-scooters for these outcomes and populations. Importantly, crime and crash both appear to be higher in areas with more older populations although the effects are not significant ($p > 0.10$). Overall, the results from the heterogeneity analysis emphasize the asymmetric effects of e-scooters based on the age and racial composition of a neighborhood.

POTENTIAL EXPLANATIONS: HEDONIC AND TOURIST ACTIVITIES

Our main results show that the entry of e-scooters has a dual impact; while it improves economic activity, it adversely impacts consumer safety and other forms of micromobility. Importantly, the effects of e-scooters are heterogeneous based on the age and racial composition of a neighborhood. Next, we explore the potential mechanisms to better understand the impact of e-scooters. Following our conceptual development in Section Related Literature and Conceptual Development, we posit that the effects may be tied with the nature of activities promoted by e-scooters, such as hedonic consumption and tourism.

To examine whether e-scooters promote certain types of economic activity (i.e., hedonic vs. functional), we split the retail categories in our main analysis (i.e., restaurants and retail stores) into sub-categories and re-estimate our models. First, we combine restaurants in the bar, coffee, and dessert categories into hedonic restaurants and the restaurants in the remaining categories into functional restaurants based on extant literature (e.g., Dhar and Wertenbroch 2000; Voss, Spangenberg, and Grohmann 2003). We categorize retail stores into large grocery chains, convenience stores, and department stores. We then estimate our DID model for each sub-category of restaurants and retail stores. The results of regressions for these sub-categories of restaurants and retail stores appear in Table 5.

Table 5: DID Model Results of the Entry of E-scooters for within Retail Visit

	Restaurant		Retail store		
Variable	Hedonic	Functional	Grocery chains	Convenience stores	Department stores
E-Scooter × Post entry (DID)	0.520***	-0.073*	0.468	0.217*	0.269***
	(0.074)	(0.038)	(0.314)	(0.127)	(0.089)
Week FE	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes
N	45,018	108,240	4,633	29,602	47,355
Adj. R^2	0.939	0.879	0.831	0.806	0.917

Notes: Robust standard errors clustered by census tract are in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.10. DID = Difference-in-Differences. FE = Fixed effects. N = No. of observations.

The results show that the entry of e-scooters increases the number of visits to restaurants categorized as hedonic but has a negative and marginally significant effect on other restaurant categories.[6] Similarly, the entry of e-scooter significantly increases the number of visits to department stores (e.g., Ross, Footlocker) but does not have a significant impact on grocery

[6]We also report the results by each category (e.g., American, Asian, Bars) in Web Appendix Table E.3 and find consistent results for the categories individually.

chains (e.g., ALDIs, Whole Foods). We also find a marginally significant positive increase in the visits to convenience stores (e.g., BP gas station stores).

While our results generally appear consistent with hedonic (vs. functional) consumption, we do not observe the nature of products and services consumers actually purchase during the visits. It is possible for a consumer to go to a dessert store (presumably hedonic) but not order or consume desserts, or to go to a grocery store (presumably functional) and purchase candy. Our data do not allow this level of detail at the consumer- or trip- level. However, we examine additional results to test if the general pattern of hedonic consumption holds.

Hedonic consumption, by virtue of being an enjoyable and pleasurable experience, should put consumers in an exploratory mindset. In this mode, consumers may be more likely to discover new or less well-known places with less existing brand presence. To examine this possibility, we carry out two types of analyses. First, we create a measure of chain vs. non-chain restaurant. Any restaurant with more than one store location is considered to be a chain and is likely to have a higher brand presence (Klopack 2022). Second, we use past visits to a restaurant before the entry of e-scooters to identify more vs. less well-known restaurants. Finally, we estimate the effects for subgroups of restaurants based on these two measures (i.e., chain vs. non-chain, and more vs. less well-known restaurants) separately.

The results of the DID regressions for these subgroups appear in Table 6. We find that the entry of e-scooters increases the relative visits to non-chain restaurants and less well-known restaurants more. This suggests that e-scooters may be facilitating restaurant discovery, and providing an impetus to local or less well-known restaurants.

So far, we have found suggestive evidence that consumers are in a more hedonic and exploration- driven mindset. These results could be consistent with enhanced tourism becuase tourists are more likely to drive hedonic consumption more than locals. To more directly investigate the effect of the entry of e-scooters on tourism, we examine four additional outcomes: Number of visits to hotels identified using SafeGraph data, number of nights available to book on Airbnb each week identified using Inside Airbnb data, and visits to

Table 6: DID Model Results of the Entry of E-scooters by Restaurant's Presence

	No. of visits			
	Non-chain	Chain	Less well-known	More well-known
E-Scooter × Post entry (DID)	0.153***	0.031	0.072***	0.137*
	(0.041)	(0.059)	(0.022)	(0.071)
Week FE	Yes	Yes	Yes	Yes
Restaurant FE	Yes	Yes	Yes	Yes
N	87,945	65,313	84,214	69,044
Adj. R^2	0.777	0.942	0.304	0.914

Notes: Robust standard errors clustered by restaurant are in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.10. DID = Difference-in-Differences. FE = Fixed effects. N = No. of observations. More (less) well-known restaurants refer to those with higher (lower) than the median number of visits in the period before the entry of e-scooters.

tourist sites (e.g., major museums) vs. local recreation sites (e.g., local parks).

The results of the DID regressions for these outcome variables appear in Table 7.[7] This Table show that the entry of e-scooters increases the number of visits to hotels, reduces the availability of Airbnb rentals, and increases the number of visits to tourist sites. However, the entry of e-scooters does not significantly impact visits to local recreation sites like parks and gyms. In Web Appendix Additional Results, we also analyze bikeshare trips by members vs. non-members, and find consistent results i.e., negative and significant effect of the entry of e-scooters on the number of bikeshare trips are driven by by non-members, rather than members, who are more likely to be local and frequent users. Collectively, these results provide support for a likely boost in hedonic and tourist activities once e-scooters enter.

[7]We also report the DID results for areas with more vs. less number of tourist sites in Web Appendix Table E.4; it shows, for example, that restaurants in census tracts with more tourist sites see a surge in visits.

Table 7: DID Model Results of the Entry of E-scooters for Tourism Sectors

Variable	Hotel	Airbnb availability	Tourist site	Local recreation
E-Scooter × Post entry (DID)	0.598*	-0.750***	0.403**	0.008
	(0.313)	(0.279)	(0.177)	(0.088)
Week FE	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes
N	3,239	6,290	14,145	42,886
Adj. R^2	0.945	0.486	0.717	0.793

Notes: Robust standard errors clustered by census tract are in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.10. DID = Difference-in-Differences. FE = Fixed effects. N = No. of observations. Airbnb availability refers to the number of nights that are available (i.e., not yet booked) in the next 30 days.

ROBUSTNESS CHECKS

In this section, we describe additional analyses to test the robustness of our main results. Specifically, we test the robustness of the results to alternative control groups, alternative identification strategies, alternative matching methods, alternative model specifications, placebo tests,and outlier observations.

Alternative Control Group and Potential Spillover to Control Areas

In general, the geo-fencing technology ensures that e-scooters are restricted within a 50-square mile treatment area defined by the city of Chicago. This institutional setting enables us to construct a clean control area, which does not allow e-scooter entry or usage. However, it is possible that individuals who want to ride e-scooters can walk or bike to the e-scooter area, particularly if they are located close to the boundary. This potential crossover, if present in our setting, could violate the stable unit of treatment value assumption (SUTVA) i.e., that there is no spillover of treatment to the control group.

To address potential spillovers, we first verify that only 1.5% of bikeshare trips start in the e-scooter and end in the non e-scooter area and our results are consistent even after excluding these trips. However, we do not observe pedestrian trips so we cannot completely address the possibility that e-scooter users can walk to the e-scooter area from a non e-scooter area. These e-scooter users from outside of the e-scooter area can drive down the outcomes, such as retail visits in the non e-scooter area and result in overestimating the effects due to the spillover to the non e-scooter area. To test the robustness of our estimates in the presence of a potential SUTVA violation, we repeat our analysis by excluding a buffer area around the e-scooter border. We define the width of the buffer area as the average distance of e-scooter trips, i.e., 1.51 miles and drop the census tracts inside our outside this distance of the e-scooter boundary. The idea is to exclude the areas where the crossover between treated and control area on foot or through other forms of micromobility is most likely. Web Appendix Table D.1 shows the results of the robustness check. We find that the results are consistent with the main results after dropping the buffer regions near the boundary of the e-scooter area.

Alternative Identification Strategy: Border Discontinuity Analysis

Even though our checks show that the treatment and control regions are similar on average, it is possible that they become less similar as we move farther away from the e-scooter boundary due to potential unobservables . However, the census tracts that are closer to either side of the boundary of the e-scooter area are arguably more similar to each other. Thus, we repeat our analysis for the census tracts near the e-scooter border by only including census tracts on either side of the boundary of the e-scooter area. This analysis is in the spirit of a border discontinuity analysis (e.g., Adalja et al. 2023; Bekkerman et al. 2022; Shapiro 2018). The results of the border discontinuity analysis appear in Web Appendix Table D.2. This table shows that the results are consistent with our main analysis for each of the outcome.

Alternative Matching Methods

Our main analyses use nearest-neighbor matching. In this robustness check, we additionally include two caliper bounds for nearest-neighbor matching with (e.g., Xu et al. 2016) and use a new matching method, optimal full matching. In caliper matching, we limit the absolute distance, $\|\widehat{p}_i - \widehat{p}_j\|$, between the propensity scores of a census tract or retailer i in the treated group and j in the control groups within 0.1 and 0.2 of the standard deviation of the propensity score. For instance, the following equation shows how to get $0.2\hat{\sigma}_{\text{pscore}}$ to get closer matches (Austin 2011).

$$\|\widehat{p}_i - \widehat{p}_j\| \leqslant 0.2\hat{\sigma}_{\text{pscore}} \tag{4}$$

In addition, we use optimal full matching to create matched sets or "strata" of census tracts and retailers and minimize the total distance within each stratum based on the propensity scores. It helps achieve a better balance in covariates between two groups and reduces bias. The following equations give us the matched data.

$$\begin{aligned} \min \sum_{i,j} & d_{ij} \times w_{ij} \\ \text{s.t.} \quad & \sum_{j} w_{ij} \geq 1 \quad \forall\, i \in \text{treatment group} \\ & \sum_{i} w_{ij} \geq 1 \quad \forall\, j \in \text{control group} \end{aligned} \tag{5}$$

The objective function $\min \sum_{i,j} d_{ij} \times w_{ij}$ minimizes the total distance across all matched pairs within each stratum. The two constraints ensure that every census tract or retailer in the treatment group or control group is matched at least once. d_{ij} is the distance measure between units i and j based on their propensity scores. w_{ij} is a binary indicator where $w_{ij} = 1$ if units i and j are matched together in a stratum, and $w_{ij} = 0$ otherwise.

Web Appendix Tables D.3, D.4 and D.5 show that the results of these alternative matching methods are consistent with those in the main analyses.

Poisson Model

To ensure the robustness of our results to alternative model specifications, we estimate a Poisson regression that is better suited for discrete or count variables. Our outcome variables are in the nature of count variables i.e., the number of rideshare trips, the number of bikeshare trips, the number of restaurant visits, the number of retail store visits, the number of crimes, and the number of crashes. The results of the Poisson models for these outcome variables appear in Web Appendix Table D.6. This table shows that the results for each of the outcome are consistent with our main model with the exception of the coefficient for the number of crashes, which becomes insignificant ($p > 0.10$) but is similar in magnitude and direction as the main results.

Placebo Tests

If our main results are indeed due to the entry of e-scooters, we should not be able to replicate them under placebo tests of reassigning either the treatment units or the timing of treatment. To rule out any placebo effects, we carry out three tests in which we randomly reassign the unit and timing of treatment, the unit of treatment only, and the timing of treatment only. Web Appendix Tables D.7, D.8, and D.9 report the effects of these placebo checks. These results show that the effect of the entry of e-scooters on restaurant visits is not significant for these placebo analyses ($p > 0.10$), assuring us that the results are robust.

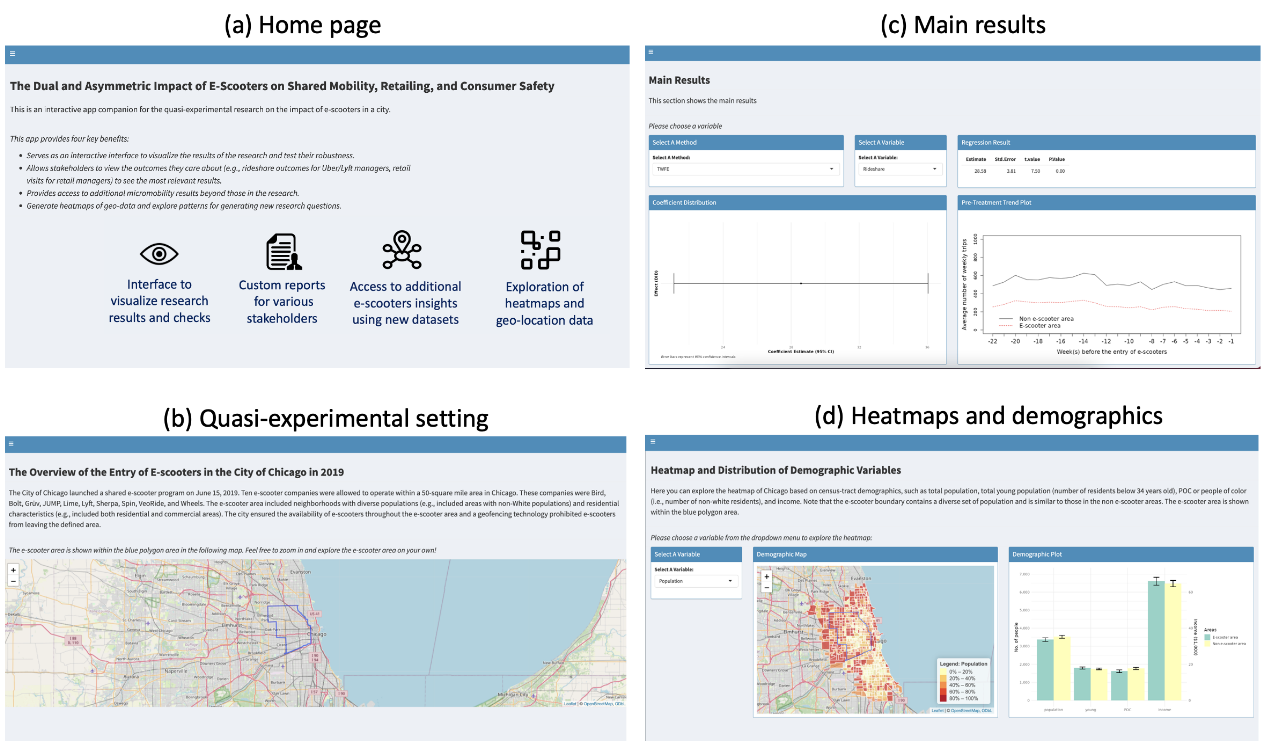
Outliers

The effects could be driven by outlier census tracts or retailers that have disproportionately more trips, retail visits, and safety concerns. To test if our main results are robust to outliers, we estimate our DID model after dropping census tracts and retailers with outlier outcome variables (the mean plus three standard deviations of outcome variables in the pre-period). The results of the model without outliers appear in Web Appendix Table D.10. This table shows that the results without outliers are consistent with our main model.

Our research is relevant for several stakeholders, including shared mobility platforms, retailers, policymakers, and cities. To make our research more accessible to these audiences and to spark more research in the areas of shared mobility and its complex impact on consumers and firms, we provide an interactive research app companion. Our research is well suited for an app like this both due to the nature of our research questions examining rich economic and societal outcomes and due to the nature of geo-location mobility data, which are easier and more informative when visualized using interactive maps.

A permanent link to the research app is available at https://e-scooter.shinyapps.io/e-scooter/. The screenshots from the app showing the main functionality appear in Figure 3.

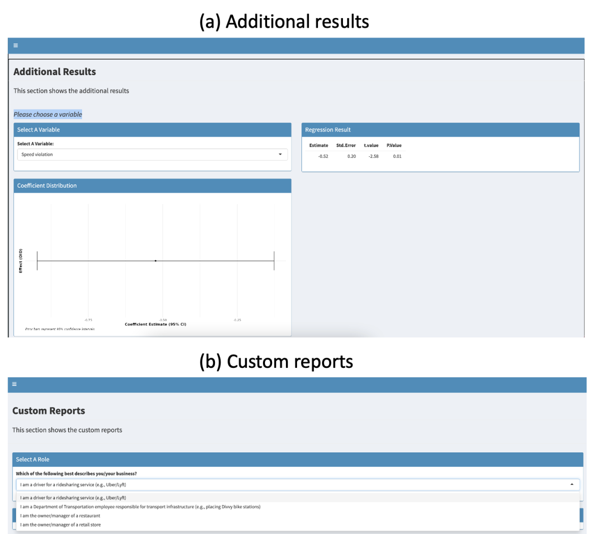
Figure 3: Screenshots from the Research App Companion: Main Features



The homepage of the app introduces the user to its key functionalities of visualizing research, customizing reports, accessing other results not focal to the research, and exploring heatmaps with geo-location patterns. The app introduces the quasi-experimental setting of the entry of e-scooters and the e-scooter boundary area on an interactive map of Chicago. It shows the distribution of demographics inside and outside the e-scooter area along with an interactive heatmap to examine the demographic distribution of race, income, population, and young population in Chicago as it relates to the e-scooter boundary.

In addition to the main features directly related to our research, the app also provides two advanced features. These are shown in Figure 4. First, the additional results page in the app reports results for the effects on parking violation and taxi trips beyond the outcomes included in the research paper. In this way, the app allows us to expand the scope of the research without detracting it. Second, the custom reports page in the app allows users to select the description that best fits their role (e.g., restaurant manager). Once the user selects their role, they are shown the relevant results and research implications.

Figure 4: Screenshots from the Research App Companion: Additional Features



Based on the overview of the research app, its four key benefits are as follows. First, the app extends the contribution of the research by providing an interactive interface to visualize the results from our research and gain additional insights. Second, it allows stakeholders to view custom reports. Third, it documents additional analyses for a new set of variables (e.g., parking violations, taxi service) not focal to the paper. Finally, it serves as a visualization tool to explore heatmaps and patterns in the data for generating new research questions.

CONCLUSION, IMPLICATIONS, AND LIMITATIONS

In this research, we addressed three research questions: First, what is the impact of the entry of e-scooters in a city on other shared mobility (i.e., rideshare and bikeshare trips), retail visits (i.e., visits to restaurant and retail stores), and consumer safety (i.e., crimes and crashes). Second, how do the effects vary by the types of neighborhoods based on the age and racial composition? Finally, what mechanisms related to the nature of consumption explain these effects?

By examining the effects of e-scooters and their potential mechanisms, our research contributes to the literature on sharing economy and micromobility, and the literature on the social and enviornmental impact of marketing. To our knowledge, this is the first paper to quantify the impact of the entry of e-scooters and micromobility on economic and societal outcomes within a city. We leverage the entry of e-scooters in Chicago in 2019 as the research context, which serves as a quasi-experiment for our research questions.

Our results show that the entry of e-scooters significantly improves economic activity but adversely impacts consumer safety and other shared micromobility (i.e., bikeshare trips). The effects appear to be driven by increase in hedonic activities and tourism. Importantly, we explore the heterogeneity in effects by neighborhood characteristics. Specifically, the benefits of e-scooters are attenuated and their downsides are aggravated for areas with relatively older populations (i.e., above the median age of 34 years) and people of color (i.e., majority non-white population).

Implications for Theory

The results from our research on the impact of the entry of e-scooters provide rich insights regarding how new forms of micromobility introduced by cities impact economic and societal outcomes. First, we expand the scope of the literature on sharing economy to micromobility services, such as e-scooters; so far, majority of the sharing economy research has focused on ride- and home-sharing platforms. Second, within the emerging but nascent micromobility studies, we also broaden the lens with which to view these technologies. We examine outcomes beyond the food sector that has been the focus of micromobility research so far. Importantly, we examine socially-relevant outcomes related to consumer safety, which is increasingly important for managers but less explored in the marketing literature. We also demonstrate how e-scooters impact other forms of shared mobility, uniquely documenting how platforms within the sharing economy can impact one another in competing or complementary ways. Finally, our results on the asymmetric effects for relatively older populations and people of color add to the growing body of work on the inequitable impact of marketing interventions.

From the perspective of theoretically advancing the marketing literature, our findings suggest a dual and asymmetric impact of e-scooters and highlight that technologies that generally appear to expand the local economy may have important unintended downsides. Physical harm, injury, and material loss in the form of crashes and crimes resulting to consumers from engagement with new technologies is an important and consequential area of investigation. Our research opens up future areas of inquiry by bringing the complex economic and societal outcomes of new mobility innovations into the purview of marketing's impact on consumers, firms, and society.

Finally, our research uniquely ties together the research in marketing with related work in transportation, energy, and urban economics. It opens the door for future inter-disciplinary research collaborations. Many of our results expand the extant knowledge in these related fields. Our results on bikesharing, for example, are consistent with estimates from a recent transportation study that shows a decrease of 23 bikeshare trips per week through a station-level analysis (Yang et al. 2021). Importantly, we also document novel results in terms of an increase in ride-share trips contrary to expected effects (Asensio et al. 2022). Finally, our work provides new evidence complementary to research on the unequal effects of infrastructure for predominantly black neighborhoods (Currier, Glaeser, and Kreindler 2023).

Implications for Practice

Micromobility is growing at unprecedented rates globally. Within micromobility, e-scooters comprise 63% of shared micromobility trips (NACTO 2022). E-scooters have several unique characteristics, such as docklessness that distinguish them from bikes and e-bikes. They also provide leisure and thrill in addition to being a means for commuting. However, they also have drawbacks, such as high risk of injury, public nuisance, and crime. This research examines the effect of the entry of e-scooters on economic and societal outcomes using a quasi-experiment in Chicago. Our findings about the effect of the entry of e-scooters and its underlying mechanisms have several important implications for shared mobility platforms, retailers, policymakers, and cities.

First, our results on the complementarity and substitution between e-scooters and other forms of shared mobility can guide mobility platforms (e.g., Uber, Divvy) in their service placement and customer engagement efforts in response to the introduction of e-scooters in a city. Uber drivers, for example, can pre-empt higher demand for short trips in areas with e-scooters and plan their locations and hours of Uber service accordingly.

Second, our finding that visits to restaurants and retail stores increase due to the entry of e-scooters suggests that stores should plan for more visitors and potentially higher revenues during the e-scooter introduction and peak usage periods. One strategy stores might use is to collaborate with e-scooter companies. They can provide discounts to e-scooter users or offer targeted advertisements via an e-scooter app, particularly during peak usage hours.

Third, within restaurants, our finding that the effects of the entry of e-scooters are the strongest for hedonic food categories, for non-chain, and for less well-known restaurants suggests that these restaurants can leverage e-scooters for creating brand awareness and getting more walk-ins. They can also predict visits better and can improve their operations, such as hiring the right number of salespersons or staff based on peak usage periods of the e-scooters. This can potentially help new businesses reduce their costs and improve their operational efficiency. In general, the finding that certain types of restaurants gain more visits from the entry of e-scooters can help both restaurants and e-scooter companies develop their marketing strategy. E-scooter companies, for example, can collaborate with coffee, dessert, and drinking places. E-scooter companies can also offer food discounts or ride discounts for consumers to these places.

Fourth, within retail stores, our finding that the effects of the entry of e-scooters are the strongest for department stores (rather than grocery chains or convenience stores) suggests that these departments stores can leverage e-scooter entry in their areas for attracting more customers and taking advantage of unplanned foot traffic.

Fifth, our research has implications for policymakers. Our research shows that e-scooters are more likely to be used for leisure activities. Policymakers should consider this before they decide to allocate e-scooters in the city. Introducing these e-scooters in districts with more restaurants, department stores, and tourist spots may be an effective strategy. However, they should be wary of the increased crime and crashes and institute precautionary measures.

Finally, our research has important implications for public policy and cities introducing e-scooter programs to improve equity and access by suggesting that e-scooters have asymmetric effects on various populations and that the non-White and older populations do not receive the benefits of expanded economic activity. In fact, crashes increase more in areas with more people of color due to e-scooter entry. Local governments should consider the need for e-scooters in different areas based on the nature of their residents to allocate e-scooter fleets equitably and incentivize their use.

Limitations

Although our research is among the first to quantify the impact of the entry of e-scooters on economic and societal outcomes within a city and the potential mechanisms, it has some limitations. First, we do not have individual-level data on each shopper's visits to and spending at different retailers and restaurants. As such, we cannot observe if these visits are from new or repeat customers. If data are available, future research can examine visits from new and existing customers. Second, even though we have a rich set of variables and datasets combined from various sources, they mainly pertain to one city's e-scooter program. Future research can replicate our results for other cities if such data are available. Third, while we are able to analyze key dimensions of heterogeneity based on age and race as well as show additional analysis on income, we do not have any data on gender. Future research may be able to capture gender differences if such data are available in other shared mobility contexts and settings. Finally, while we conduct various checks to examine the exogeneity of the entry of e-scooters as well as a variety of robustness checks, if there are any omitted factors that are correlated with both the city's strategy for launching e-scooters in certain areas and the retail visit likelihood in those areas, our estimates should be best interpreted as descriptive. If opportunities to conduct large-scale field experiments are available, future research can leverage randomization to recover such effects, e.g., by manipulating the availability of e-scooters in different neighborhoods, or nudges via e-scooter apps.

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Web Appendix

The Dual and Asymmetric Impact of E-Scooters on Shared Mobility, Retailing, and Consumer Safety

AMA Disclosure: These materials have been supplied by the authors to aid in the understanding of their paper. The AMA is sharing these materials at the request of the authors.

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A Example of Companies Included in Analysis

Table A.1: Example of Businesses in the Restaurant and Retail Categories in Our Data

Categories	Business names
Restaurant	
Hedonic restaurants	Starbucks, Baskin Robbins, Au Bon Pain, La Michoacana, Forever Yogurt, Xurro, Intelligentsia Coffee, La Colombe, Kanela Breakfast Club, Dairy Queen, Somethin' Sweet Donuts, Black Dog Gelato, Margie's Candies, Do Rite Donuts & Chicken, Tropical Smoothie Café, Bridgeport Coffee, Emerald City Coffee, Emerald City Coffee, La Catedral Cafe & Restaurant, Bridgeport Coffee, Lickity Split Frozen Custard, Bang Bang Pie & Biscuits, Jeni's Splendid Ice Creams
Functional restaurants	Subway, Burger King, Popeyes Louisiana Kitchen, Jimmy John's, Domino's Pizza, Chipotle Mexican Grill, KFC, Taco Bell, Potbelly Sandwich Works, Wingstop, Wendy's, Little Caesars, White Castle, See Thru Chinese Kitchen, Church's Chicken, Farmer's Fridge, Sweetgreen, Pizza Hut, Giordano's, Papa John's, Checkers Drive-In Restaurants, Jet's Pizza, Panda Express, IHOP, Lou Malnati's Pizzeria, Golden Nugget Pancake House, Taco Burrito King, Sarpino's Pizzeria, Krispy Krunchy Chicken
Retail store	
Grocery chains	Family Dollar Stores, Dollar Tree, ALDI, Dollar General, Mariano's, Jewel-Osco, Cermak Fresh Market, Five Below, Walmart, Costco Wholesale Corp., Fresh Market Place, Whole Foods Market, Trader Joe's, Sam's Club
Convenience stores	BP, Shell Oil, 7-Eleven, Mobil, CITGO, Marathon, Tony's Finer Foods, Binny's Beverage Depot, Gulf Oil, Dulcelandia, Save-A-Lot, Falcon Fuel, Foremost Liquors, Thorntons, La Chiquita Food Market, Pete's Market, Leamington Foods, Lush Wine and Spirits, Food 4 Less, Speedway, Farmer's Best Market, Top Less Liquor, Mom & Son's Food Mart, Snack 4 Less, Super Mercado Brisa Foods, Peerless Liquors, Foxtrot Market West Loop
Department stores	Rainbow Shops, Target, Foot Locker, Ross Stores, Edible Arrangements, Village Discount Outlet, Botanica La Ceiba, Marshalls, Ferguson, Party City, Escaramuza USA, Cemirex, Tops & Bottoms, Ashland Addison Florist, Very Best Vintage, Fleur

Notes: The names of the businesses come from the SafeGraph *Places* data. However, we categorize them as described in the paper. Hedonic restaurants include coffee, bars, and dessert places while functional restaurants include all other categories.

B Restaurant Categories

Table B.1: The Categories of Restaurants using Yelp API

ID	Categories	Description	Popular tags
1	American	Restaurants serving American cuisine, but excluding restaurants specializing in burgers and sandwiches, and excluding restaurants that were also tagged as another type.	American (Traditional), American (new), Breakfast, Brunch, Chicken wings, Diners
2	Asian	Restaurants specializing in cuisines from south Asian, east Asian, and Southeast Asian countries, as well as pacific islands.	Chinese, Japanese, Sushi bars, Asian fusion, Thai, Indian, Hawaiian
3	Bars	Restaurants with "Bar", "Pub", "Late Night", etc.	Bar, Pub, Late Night
4	Burgers	Restaurants with tag "Burgers".	Burgers, Hot dogs, Sports bars, Steakhouses
5	Coffee	Restaurants with tag "Coffee".	Coffee, Café
6	Dessert	Restaurants with tag "Dessert".	Dessert, Frozen yogurt
7	European	Restaurants specializing in Italian, French, or other European cuisines, except for restaurants also tagged "Pizza".	Italian, French, Irish, Wine Bars, Noodles, Mediterranean
8	Latin American	Restaurants specializing in cuisines from south and central America and the Caribbean.	Mexicana, Tex-Mex, Latín American, seafood, Caribbean, Cuban
9	Pizza	Restaurants with tag "Pizza". Pizza, Italian, salad	Pizza
10	Sandwiches	Restaurants with tag "Sandwiches", "Deli", or "Cheesesteaks".	Sandwiches, Deli, Cheesesteaks

Notes: Refer to Klopack (2022)

C Additional Results on Selection Concerns

In this section, we report the pre-entry trends for each dependent variable individually. We also report the propensity score matching (PSM) analysis.

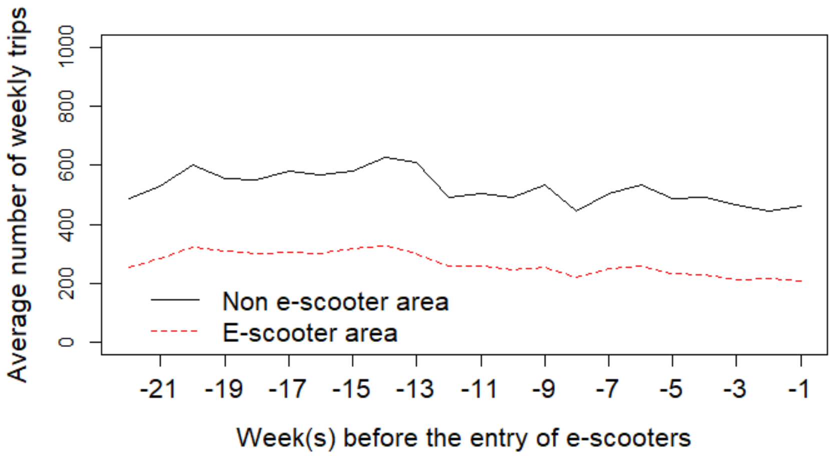

Figure C.1: Pre-period Trends of Rideshare Trips in the Treatment and Control Areas

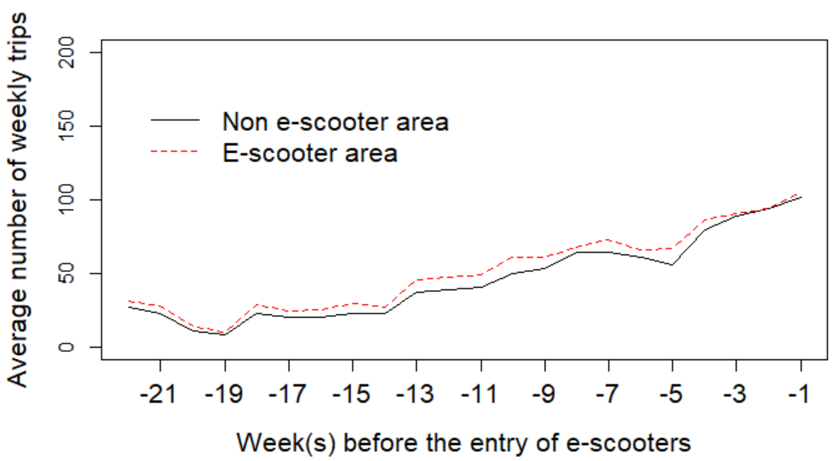

Figure C.2: Pre-period Trends of Bikeshare Trips in the Treatment and Control Areas

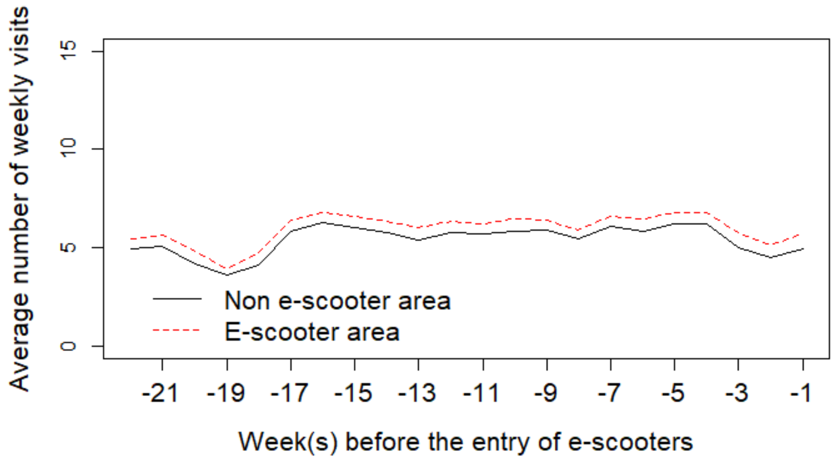

Figure C.3: Pre-period Trends of the Number of Restaurant Visits in the Treatment and Control Areas

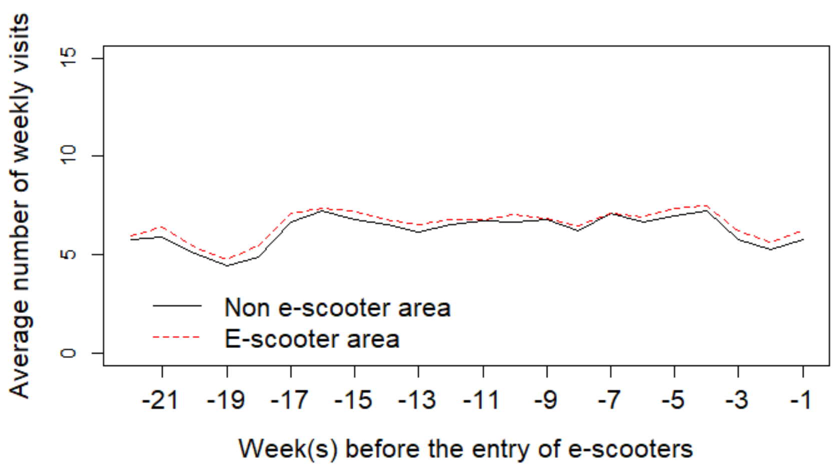

Figure C.4: Pre-period Trends of the Number of Retail Store Visits in the Treatment and Control Areas

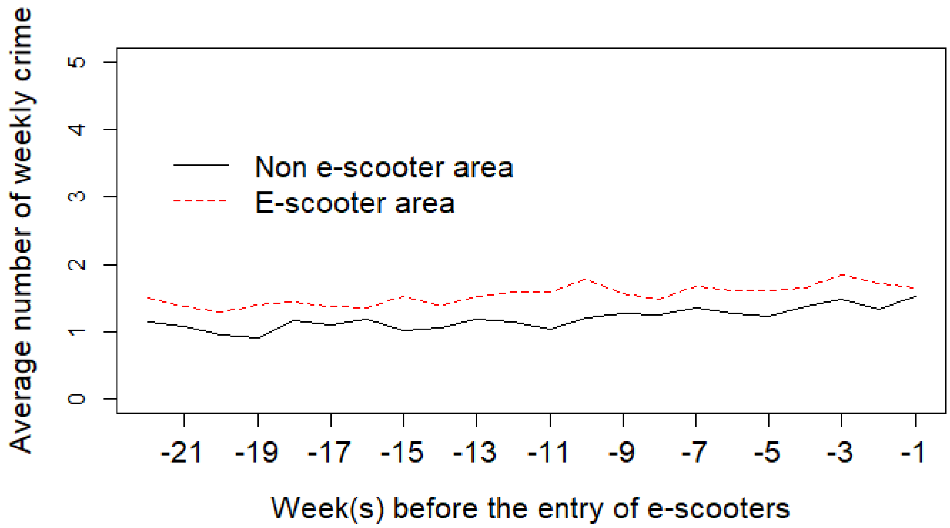

Figure C.5: Pre-period Trends of the Number of Crimes in the Treatment and Control Areas

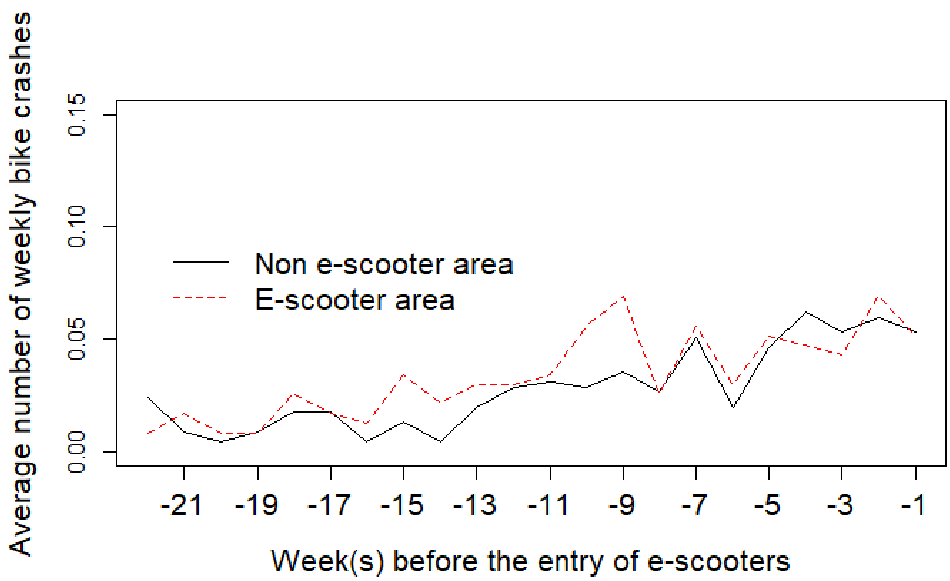

Figure C.6: Pre-period Trends of the Number of Crashes in the Treatment and Control Areas

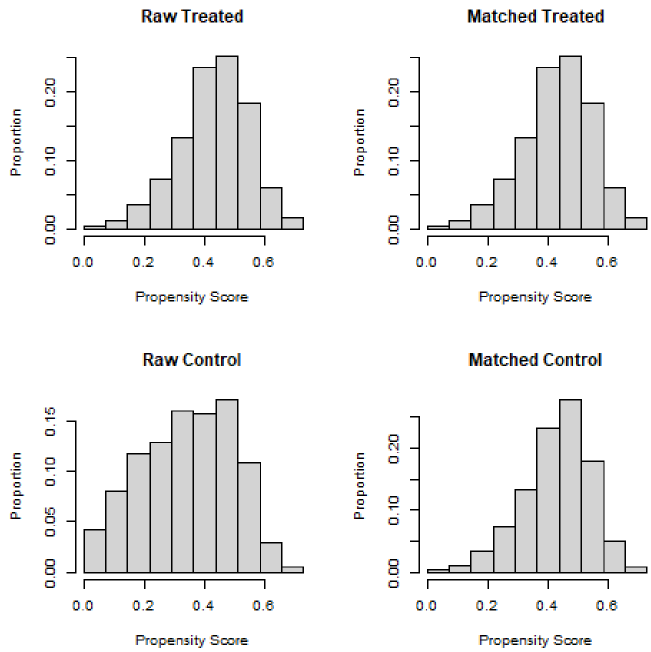

Figure C.7: Distribution of Propensity Scores for Rideshare Before and After Matching

Notes: The plots of raw treated and raw control show pre-matching propensity scores.

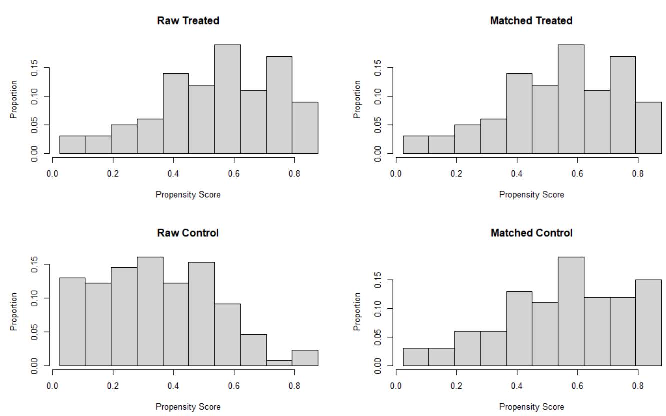

Figure C.8: Distribution of Propensity Scores for Bikeshare Before and After Matching

Notes: The plots of raw treated and raw control show pre-matching propensity scores.

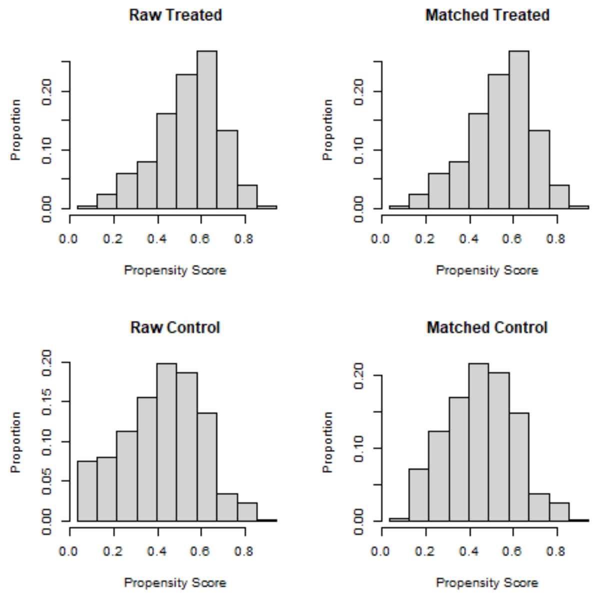

Figure C.9: Distribution of Propensity Scores for the Number of Restaurant Visits Before and After Matching

Notes: The plots of raw treated and raw control show pre-matching propensity scores.

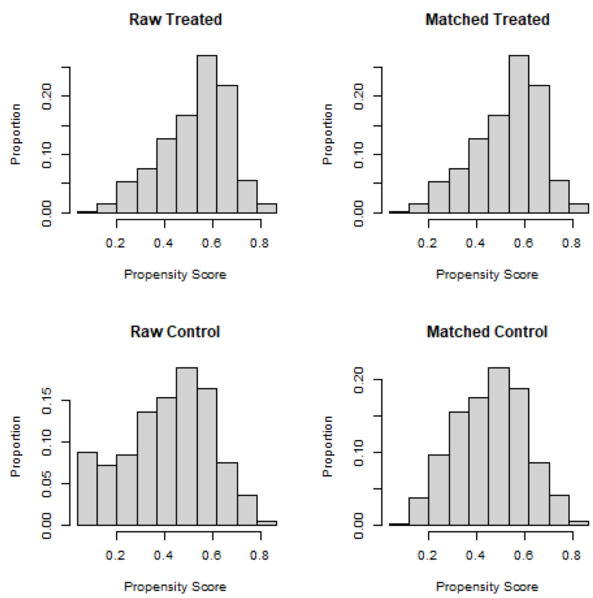

Figure C.10: Distribution of Propensity Scores for the Number of Retail Store Visits Before and After Matching

Notes: The plots of raw treated and raw control show pre-matching propensity scores.

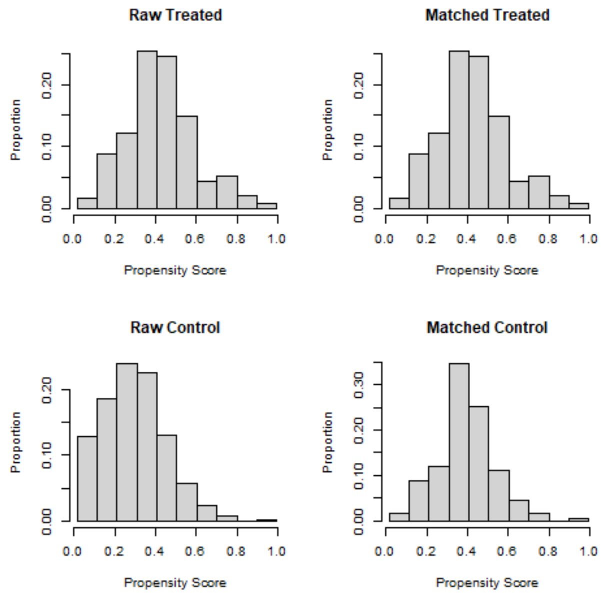

Figure C.11: Distribution of Propensity Scores for the Number of Crimes Before and After Matching

Notes: The plots of raw treated and raw control show pre-matching propensity scores.

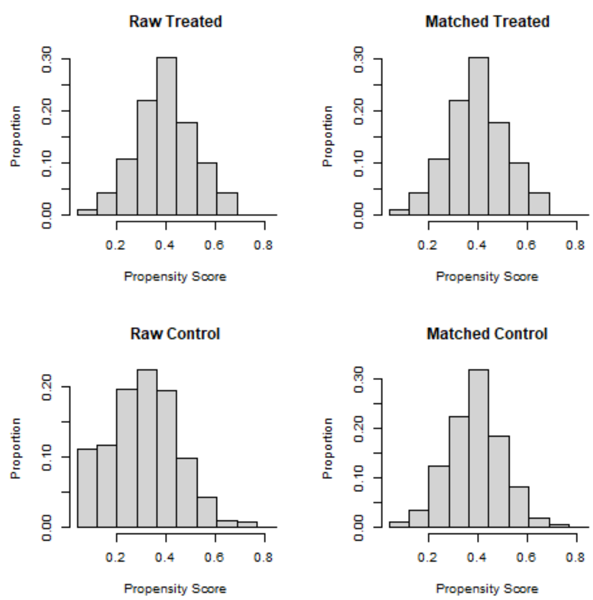

Figure C.12: Distribution of Propensity Scores for the Number of Crashes Before and After Matching

Notes: The plots of raw treated and raw control show pre-matching propensity scores.

Table C.1: Summary of Balance Before and After Matching for Rideshare

	Before matching			After matching		
Variable	Means control	Means treated	p-value	Means control	Means treated	p-value
log_population	7.996	7.987	0.836	7.990	7.987	0.952
log_income	10.901	10.951	0.251	10.951	10.951	0.990
log_POC	7.183	7.094	0.155	7.093	7.094	0.287
log_young	7.274	7.349	0.094	7.343	7.349	0.906

Notes: We also included the past values of the outcome variable for the pre-entry period but do not report them to save space. POC = the people of color. Young population is the number of inhabitants under 34 years old.

Table C.2: Summary of Balance Before and After Matching for Bikeshare

	Before matching			After matching		
Variable	Means control	Means treated	p-value	Means control	Means treated	p-value
log_population	8.024	7.939	0.219	8.013	7.939	0.184
log_income	10.829	11.061	0.003	10.963	11.061	0.783
log_POC	7.203	6.918	0.010	7.075	6.918	0.287
log_young	7.302	7.352	0.094	7.362	7.352	0.236

Notes: We also included the past values of the outcome variable for the pre-entry period but do not report them to save space. POC = the people of color. Young population is the number of inhabitants under 34 years old.

Table C.3: Summary of Balance Before and After Matching for Restaurant

	Before matching			After matching		
Variable	Means control	Means treated	p-value	Means control	Means treated	p-value
log_population	8.201	8.173	0.068	8.223	8.173	0.002
log_income	11.014	11.175	0.001	11.047	11.175	0.001
log_POC	7.218	7.055	0.001	7.173	7.055	0.001
log_young	7.492	7.573	0.001	7.540	7.573	0.040

Notes: We also included the past values of the outcome variable for the pre-entry period and restaurant category information but do not report them to save space. POC = the people of color. Young population is the number of inhabitants under 34 years old.

Table C.4: Summary of Balance Before and After Matching for Retail stores

	Before matching			After matching		
Variable	Means control	Means treated	p-value	Means control	Means treated	p-value
log_population	8.173	8.155	0.292	8.147	8.155	0.750
log_income	10.970	11.069	0.001	10.970	11.069	0.001
log_POC	7.279	7.135	0.001	7.240	7.135	0.009
log_young	7.452	7.532	0.001	7.495	7.532	0.149

Notes: We also included the past values of the outcome variable for the pre-entry period and retailer category information but do not report them to save space. POC = the people of color. Young population is the number of inhabitants under 34 years old.

Table C.5: Summary of Balance Before and After Matching for Crime

	Before matching			After matching		
Variable	Means control	Means treated	p-value	Means control	Means treated	p-value
log_population	8.018	7.978	0.350	7.971	7.978	0.878
log_income	10.927	10.934	0.872	10.939	10.934	0.916
log_POC	7.173	7.102	0.260	7.044	7.102	0.424
log_young	7.293	7.342	0.272	7.325	7.342	0.758

Notes: We also included the past values of the outcome variable for the pre-entry period but do not report them to save space. POC = the people of color. Young population is the number of inhabitants under 34 years old.

Table C.6: Summary of Balance Before and After Matching for Crash

	Before matching			After matching		
Variable	Means control	Means treated	p-value	Means control	Means treated	p-value
log_population	7.992	7.955	0.400	7.967	7.955	0.838
log_income	10.913	10.910	0.943	10.948	10.910	0.519
log_POC	7.162	7.095	0.303	7.024	7.095	0.419
log_young	7.273	7.329	0.220	7.323	7.329	0.910

Notes: We also included the past values of the outcome variable for the pre-entry period but do not report them to save space. POC = the people of color. Young population is the number of inhabitants under 34 years old.

Table C.7: Estimates by Week for the Pre-Entry Week

	Shared mobility		Retail visits		Consumer safety	
Variable	Rideshare	Bikeshare	Restaurant	Retail store	Crime	Crash
E-Scooter × week -23	-1.308	2.350	0.031	0.082	-0.010	-0.013
	(9.786)	(25.254)	(0.141)	(0.387)	(0.163)	(0.022)
E-Scooter × week -22	-1.293	5.380	0.087	0.113	0.000	-0.004
	(17.555)	(28.030)	(0.143)	(0.377)	(0.159)	(0.022)
E-Scooter × week -21	-19.456	6.850	-0.231	0.547	0.200	-0.017
	(13.303)	(28.283)	(0.157)	(0.390)	(0.159)	(0.021)
E-Scooter × week -20	5.677	1.890	0.115	0.264	-0.177	-0.004
	(12.862)	(25.499)	(0.136)	(0.396)	(0.164)	(0.024)
E-Scooter × week -19	7.696	4.610	0.028	-0.291	0.000	-0.004
	(13.493)	(26.237)	(0.149)	(0.449)	(0.157)	(0.024)
E-Scooter × week -18	4.171	3.590	0.037	-0.758	-0.116	-0.004
	(12.373)	(26.091)	(0.156)	(0.444)	(0.162)	(0.022)
E-Scooter × week -17	8.357	3.050	-0.005	0.133	0.337**	-0.004
	(12.356)	(25.132)	(0.151)	(0.458)	(0.158)	(0.029)
E-Scooter × week -16	10.700	2.640	0.005	-0.337	0.112	0.000
	(14.615)	(24.986)	(0.146)	(0.454)	(0.158)	(0.024)
E-Scooter × week -15	-19.000	2.760	0.081	-0.354	0.044	0.013
	(14.285)	(22.794)	(0.146)	(0.448)	(0.165)	(0.024)
E-Scooter × week -14	19.453***	3.830	0.056	-0.613	0.104	-0.004
	(6.775)	(22.656)	(0.148)	(0.474)	(0.168)	(0.025)
E-Scooter × week -13	8.076	7.230	-0.013	-0.865*	0.321	-0.004
	(8.262)	(22.208)	(0.149)	(0.479)	(0.170)	(0.026)
E-Scooter × week -12	5.635	0.180	0.082	-0.150	0.229	-0.004
	(6.297)	(20.783)	(0.148)	(0.405)	(0.174)	(0.036)
E-Scooter × week -11	-23.270***	-7.580	-0.035	-0.955*	-0.020	0.047*
	(8.684)	(19.658)	(0.148)	(0.399)	(0.170)	(0.025)
E-Scooter × week -10	6.620***	-9.750	-0.150	-0.381	-0.056	-0.009
	(7.261)	(19.012)	(0.158)	(0.389)	(0.170)	(0.027)
E-Scooter × week -9	1.148	-9.100	-0.016	-0.999**	-0.116	-0.013
	(6.804)	(19.375)	(0.150)	(0.493)	(0.175)	(0.031)
E-Scooter × week -8	-5.080	-10.850	0.108	-0.247	0.016	0.013
	(6.961)	(18.674)	(0.145)	(0.369)	(0.163)	(0.021)
E-Scooter × week -7	-2.601	-8.070	0.035	-0.074	0.040	-0.022
	(6.281)	(19.408)	(0.149)	(0.382)	(0.161)	(0.033)
E-Scooter × week -6	-2.810	-10.910	0.071	-0.145	0.028	0.009
	(6.596)	(19.219)	(0.156)	(0.470)	(0.169)	(0.027)
E-Scooter × week -5	-8.669	-24.030	0.223	0.147	0.120	0.013
	(8.385)	(22.753)	(0.141)	(0.387)	(0.182)	(0.023)
E-Scooter × week -4	-11.099	-14.510	0.087	0.176	0.129	0.022
	(8.873)	(18.803)	(0.141)	(0.381)	(0.163)	(0.030)
E-Scooter × week -3	-6.901	-27.750	0.225	0.071	-0.133	-0.004
	(7.951)	(25.436)	(0.139)	(0.366)	(0.169)	(0.032)
E-Scooter × week -2	-7.369	-7.220	0.335**	-0.027	0.064	0.004
	(7.000)	(18.698)	(0.140)	(0.353)	(0.167)	(0.038)
E-Scooter × week -1	-2.449	-14.350	0.273*	0.020	-0.193	0.047*
	(7.639)	(25.727)	(0.143)	(0.406)	(0.170)	(0.028)
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes
N	21,566	6,150	153,258	81,590	20,418	15,785
Adj. R^2	0.967	0.800	0.913	0.879	0.517	0.084

Notes: Robust standard errors clustered by census tract are in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.10. DID = Difference-in-Differences. FE = Fixed effects. N = No. of observations.

D Robustness Checks

Table D.1: DID Model Results of the Entry of E-scooters for SUTVA

	Shared mobility		Retail visits		Consumer safety	
Variable	Rideshare	Bikeshare	Restaurant	Retail Store	Crime	Crash
E-Scooter × Post entry (DID)	26.142***	-22.028**	0.040**	0.040**	0.137***	0.018*
	(2.042)	(5.945)	(0.014)	(0.016)	(0.047)	(0.011)
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes
N	16,359	4,551	119,064	62,197	15,088	11,931
Adj. R^2	0.958	0.785	0.429	0.575	0.483	0.070

Notes: Robust standard errors clustered by census tract are in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.10. DID = Difference-in-Differences. FE = Fixed effects. N = No. of observations.

Table D.2: DID Model Results of the Entry of E-scooters for Border Discontinuity Analysis

	Share mobility		Retail visits		Consumer safety	
Variable	Rideshare	Bikeshare	Restaurant	Retail Store	Crime	Crash
E-Scooter × Post entry (DID)	20.967***	-29.620***	0.059***	0.042**	0.231***	0.020**
	(2.911)	(4.176)	(0.014)	(0.018)	(0.041)	(0.010)
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes
N	17,548	5,207	125,911	73,677	16,892	13,858
Adj. R^2	0.969	0.823	0.454	0.523	0.524	0.080

Notes: Robust standard errors clustered by census tract are in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.10. DID = Difference-in-Differences. FE = Fixed effects. N = No. of observations.

Table D.3: DID Model Results with Nearest-Neighbor Matching within the Caliper = 0.1

	Share mobility		Retail visits		Consumer safety	
Variable	Rideshare	Bikeshare	Restaurant	Retail store	Crime	Crash
E-Scooter × Post entry (DID)	13.353***	-15.271***	0.120***	0.546***	0.108***	0.022**
	(2.521)	(4.986)	(0.041)	(0.106)	(0.038)	(0.010)
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes
N	21,320	5,822	112,832	81,262	18,286	15,703
Adj. R^2	0.967	0.802	0.839	0.881	0.434	0.083

Notes: Robust standard errors clustered by census tract are in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. DID = Difference-in-Differences. FE = Fixed effects. N = No. of observations.

Table D.4: DID Model Results with Nearest-Neighbor Matching within the Caliper = 0.2

	Share mobility		Retail visits		Consumer safety	
Variable	Rideshare	Bikeshare	Restaurant	Retail store	Crime	Crash
E-Scooter × Post entry (DID)	12.792***	-13.527***	0.153***	0.532***	0.128***	0.021**
	(2.506)	(4.894)	(0.039)	(0.106)	(0.038)	(0.010)
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes
N	21,566	6,068	122,590	81,508	19,024	15,744
Adj. R^2	0.967	0.802	0.839	0.879	0.460	0.085

Notes: Robust standard errors clustered by census tract are in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. DID = Difference-in-Differences. FE = Fixed effects. N = No. of observations.

Table D.5: DID Model Results with Optimal Full Matching

	Share mobility		Retail visits		Consumer safety	
Variable	Rideshare	Bikeshare	Restaurant	Retail store	Crime	Crash
E-Scooter × Post entry (DID)	20.524***	-16.535***	0.259***	0.444***	0.175***	0.023**
	(2.977)	(4.990)	(0.091)	(0.095)	(0.051)	(0.008)
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes
N	28,577	9,471	160,515	130,052	30,094	20,131
Adj. R^2	0.975	0.776	0.913	0.885	0.562	0.087

Notes: Robust standard errors clustered by census tract are in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. DID = Difference-in-Differences. FE = Fixed effects. N = No. of observations.

Table D.6: Poisson Model Results of the Entry of E-scooters

	Share mobility		Retail visits		Consumer safety	
Variable	Rideshare	Bikeshare	Restaurant	Retail store	Crime	Crash
E-Scooter × Post entry (DID)	0.067***	-0.033**	0.032***	0.040***	0.070***	0.230
	(0.006)	(0.016)	(0.006)	(0.011)	(0.025)	(0.149)
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes
N	21,566	6,150	153,258	81,385	20,049	11,931
Log pseudolikelihood	-116,441.1	-25,344.9	-320,381.6	-178,090.6	-28,054.5	-2,851.3

Notes: Robust standard errors clustered by census tract are in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. DID = Difference-in-Differences. FE = Fixed effects. N = No. of observations.

Table D.7: Placebo Test for Both Week and Treatment

	Share mobility		Retail visits		Consumer safety	
Variable	Rideshare	Bikeshare	Restaurant	Retail store	Crime	Crash
E-Scooter × Post entry (DID)	5.875	-0.888	-0.045	0.273	0.071	0.019
	(9.651)	(8.639)	(0.095)	(0.225)	(0.103)	(0.018)
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes
N	12,098	3,450	85,974	45,770	11,454	8,855
Adj. R^2	0.976	0.772	0.928	0.905	0.515	0.056

Notes: Robust standard errors clustered by census tract are in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.10. DID = Difference-in-Differences. FE = Fixed effects. N = No. of observations.

Table D.8: Placebo Test for Treatment Only

	Share mobility		Retail visits		Consumer safety	
Variable	Rideshare	Bikeshare	Restaurant	Retail store	Crime	Crash
E-Scooter × Post entry (DID)	0.684	2.039	-0.032	-0.015	0.008	-0.010
	(2.508)	(2.784)	(0.035)	(0.061)	(0.039)	(0.008)
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes
N	21,566	6,150	153,258	81,590	20,418	15,785
Adj. R^2	0.967	0.817	0.913	0.877	0.516	0.079

Notes: Robust standard errors clustered by census tract are in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.10. DID = Difference-in-Differences. FE = Fixed effects. N = No. of observations.

Table D.9: Placebo Test for Week Only

	Share mobility		Retail visits		Consumer safety	
Variable	Rideshare	Bikeshare	Restaurant	Retail store	Crime	Crash
E-Scooter × Post entry (DID)	12.610	7.635	-0.047	-0.141	0.071	-0.001
	(9.639)	(10.500)	(0.095)	(0.298)	(0.103)	(0.020)
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes
N	12,098	3,450	85,974	45,770	11,454	8,855
Adj. R^2	0.976	0.772	0.928	0.905	0.515	0.056

Notes: Robust standard errors clustered by census tract are in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.10. DID = Difference-in-Differences. FE = Fixed effects. N = No. of observations.

Table D.10: DID Model Results of the Entry of E-scooters without Outliers

	Share mobility		Retail visits		Consumer safety	
Variable	Rideshare	Bikeshare	Restaurant	Retail store	Crime	Crash
E-Scooter × Post entry (DID)	19.339***	-20.332**	0.097**	0.132*	0.152***	0.020**
	(1.608)	(4.902)	(0.031)	(0.073)	(0.038)	(0.010)
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes
N	21,115	6,068	151,577	80,647	20,213	15,785
Adj. R^2	0.960	0.781	0.761	0.792	0.455	0.085

Notes: Robust standard errors clustered by census tract are in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.10. DID = Difference-in-Differences. FE = Fixed effects. N = No. of observations.

E Additional Results

Table E.1: DID Model Results of the Entry of E-Scooters for Heterogeneity by Income and Age

	Shared mobility		Retail visits		Consumer safety	
Variable	Rideshare	Bikeshare	Restaurant	Retail store	Crime	Crash
DID	10.906***	4.731	-0.026	0.263	0.129	0.023
	(2.783)	(6.902)	(0.065)	(0.165)	(0.079)	(0.016)
DID × High Older	15.612***	-25.400***	-0.106	-0.570***	0.021	0.004
	(4.645)	(7.561)	(0.082)	(0.200)	(0.078)	(0.019)
DID × High Income	-7.685*	-16.934**	0.189**	0.915***	0.055	-0.010
	(4.588)	(7.679)	(0.075)	(0.210)	(0.078)	(0.019)
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes
N	21,566	6,150	153,258	81,590	20,418	15,785
Adj. R^2	0.968	0.820	0.913	0.879	0.516	0.087

Notes: Robust standard errors clustered by census tract are in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. DID = Difference-in-Differences. FE = Fixed effects. N = No. of observations. Retail store includes retailers such as grocery chains, convenience stores, and department stores. We also include the main effects and two-way interaction terms of the moderating variables High older and High Income with each term but do not report them to save space.

Table E.2: DID Model Results of the Entry of E-scooters within Bikeshare

	Bikeshare		Rideshare trips
Variable	Member	Non-member	Long
E-Scooter × Post entry (DID)	1.697	-13.626***	21.381***
	(3.220)	(2.252)	(3.468)
Week FE	Yes	Yes	Yes
Location FE	Yes	Yes	Yes
N	6,109	5,535	28,044
Adj. R^2	0.834	0.631	0.647

Notes: Robust standard errors clustered by census tract are in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.10. DID = Difference-in-Differences. FE = Fixed effects. N = No. of observations. Long trips refer to ridesharing trips of over two miles.

Table E.3: DID Model Results of the Entry of E-scooters for Retail Visits by Restaurant

	No. of visits									
	American	Asian	Bar	Burger	Coffee	Dessert	European	Latin American	Pizza	Sandwiches
E-Scooter × Post entry (DID)	0.174	-0.079	0.545***	-0.251	0.825**	0.370*	0.401*	0.105	-0.023	-0.341
	(0.181)	(0.153)	(0.205)	(0.296)	(0.343)	(0.206)	(0.238)	(0.130)	(0.283)	(0.327)
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Restaurant FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	17,589	21,607	17,712	11,193	14,801	15,170	8,487	28,741	11,480	15,170
R^2	0.068	0.058	0.053	0.063	0.076	0.079	0.060	0.061	0.059	0.056

Notes: Robust standard errors clustered by restaurant are in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.10. DID = Difference-in-Differences. FE = Fixed effects. N = No. of observations. Results reported in this Table are for unmatched data, similar to Table **??**.

Table E.4: DID Model Results of the Entry of E-scooters for Heterogeneity within Retail by Tourism

	Shared mobility				Retail visits				Consumer safety			
	Rideshare		Bikeshare		Restaurant		Retail Store		Crime		Crash	
Variable	High-Tour	Low-Tour	High-Tour	Low-Tour	High-Tour	Low-Tour	High-Tour	Low-Tour	High-Tour	Low-Tour	High-Tour	Low-Tour
E-Scooter × Post entry (DID)	30.910***	-2.303	-13.217*	-26.648***	0.254***	-0.139***	0.605***	0.422***	0.178***	0.140**	0.029**	0.010
	(4.259)	(1.852)	(6.986)	(2.228)	(0.045)	(0.053)	(0.148)	(0.139)	(0.047)	(0.065)	(0.014)	(0.013)
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	11,316	10,250	4,346	1,804	93,685	59,573	47,765	33,825	10,988	9,430	8,528	7,257
Adj. R^2	0.965	0.973	0.810	0.820	0.933	0.807	0.885	0.857	0.471	0.516	0.096	0.054

Notes: Robust standard errors clustered by census tract are in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. DID = Difference-in-Differences. FE = Fixed effects. N = No. of observations.