How E-Scooters Impact Shared Mobility and Consumer Safety

Ruichun Liu and Unnati Narang*

Abstract

Shared micromobility services that comprise small lightweight vehicles, such as electric scooters (i.e., e-scooters) are growing rapidly. While e-scooters can offer several benefits (e.g., higher mobility, equitable access), they can also have potential downsides (e.g., risk of injury, reckless behavior). Research on micromobility in marketing shows that e-scooters boost restaurant spending, but it does not examine their effects on important economic and societal outcomes beyond the food sector. Similarly, research on the sharing economy rarely focuses on micromobility services or on demand interactions between shared platforms. Therefore, our paper examines the effects of the entry of e-scooters on other incumbent shared mobility services in the sharing economy (i.e., ridesharing and bikesharing) and on overall consumer safety (i.e., crimes and crashes). Using the entry of e-scooters in parts of Chicago in 2019 and a difference-in-differences analysis with propensity score matching, our results reveal a dual effect of e-scooters. First, the entry of e-scooters increases the number of short rideshare trips by 4.79%, but decreases the number of bikeshare trips by 13.53%. Our results on the complementary effect for ridesharing and the substitution effect for bikesharing can be explained by e-scooters' relative advantages and disadvantages, depending on the timing and type of usage. Second, the entry of e-scooters increases the number of crimes (e.g., vehicle break-ins) by 9.78% and crashes (e.g., bike crash) by 56.23%. The increase in crimes and crashes is explained by street and vehicle crimes, and by crashes involving micromobility vehicles. Importantly, the effects are heterogeneous and asymmetric by the age and racial composition of a neighborhood. Overall, e-scooters contribute about \$4.7 million in ridesharing revenues but they also have an unintended negative environmental effect amounting to about 510 metric ton carbon emissions per year. Our research offers key implications and includes an *app companion* for stakeholders.

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

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INTRODUCTION

Shared micromobility services that comprise small lightweight vehicles, such as electric scooters (i.e., e-scooters) are growing rapidly. Globally, the micromobility industry is posited to surpass $198.03 billion by 2030 (Precedence 2022). Within micromobility services, the e-scooter market (e.g., Bird, Lyft) is predicted to reach $12.4 billion by 2030 and is among the fastest growing segments with 18.9% growth (Research and Markets 2024). In the U.S., 156 cities have adopted e-scooters by 2023 compared with 87 cities in 2019 (BTS 2023).

E-scooters have the potential to impact consumer mobility and safety, which are important priorities for marketers, platforms, and cities (Chen et al. 2024; Zhang and Li 2021). On the one hand, e-scooters can offer expanded access to an alternative source of mobility in a city and increase consumption (Chu et al. 2020; Kim and McCarthy 2024). On the other hand, they can also have possible downsides, such as risk of injury and reckless behavior, which could threaten consumer safety (Oeschger, Carroll, and Caulfield 2020). Many cities introduce e-scooters to improve equitable access to mobility. For example, the city of Chicago requires e-scooters to enhance "access and opportunities for groups who have the greatest need" (Brown, Howell, and Creger 2022).[1] However, several cities have also banned or restricted e-scooters due to potential safety concerns. For example, Atlanta banned e-scooters at night after four riders were killed (Short 2019). Similarly, Paris banned e-scooters due to increased accidents (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 reactions by cities, there is little understanding of how they affect consumer mobility and safety, and how their impact varies by subgroups of population (Mays 2023). The emerging literature on micromobility in marketing seldom examines the effects of e-scooters beyond the restaurant and food industries (Kim and Kannan 2023; Kim and McCarthy 2024). Similarly, the literature on the

[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).

sharing economy rarely examines micromobility platforms and mostly focuses on ride- and home- sharing platforms (e.g., Barron, Kung, and Proserpio 2020; Zervas, Proserpio, and Byers 2017). While there is some work on how ridesharing platforms impact motor vehicle accidents and moral hazard, the issue of consumer safety is not well understood in the sharing economy literature (Greenwood and Wattal 2017; Liu, Brynjolfsson, and Dowlatabadi 2021). Furthermore, with the exception of Zhang et al. (2022), there are not a lot of studies on important demand interactions between various shared platforms. Therefore, we focus on the important economic and societal effects of the entry of shared e-scooters on incumbent shared mobility platforms in the sharing economy and on overall consumer safety.

Our research addresses three main research questions. First, how does the entry of e-scooters in a city impact important economic and societal outcomes, including incumbent shared mobility (i.e., ridesharing and bikesharing) and consumer safety (i.e., crimes and crashes)? Second, how does the impact of e-scooters vary by the type of neighborhood based on the age and racial composition of its residents (i.e., for older populations and people of color)? Finally, what mechanisms related to the timing and type of usage explain the effects of e-scooters on our key outcomes?

It is not a priori clear how e-scooters will impact incumbent shared mobility services and consumer safety. E-scooters, as new entrants in shared micromobility, have both distinct and overlapping characteristics compared to their predecessors. Compared with ridesharing, a traditional shared mobility service comprising mainly cars, e-scooters are better suited for short solo trips and are less impacted by traffic congestion, but they likely suffer from limited storage capacity for carrying items. Compared with bikesharing, another shared micromobility service, e-scooters can offer faster speeds with much less physical effort along with better last-mile reach. Based on these characteristics, e-scooters may offer relative advantages or disadvantages depending on the timing and type of usage compared with ridesharing and bikesharing, resulting in different impacts on these services. In addition to their effects on incumbent shared mobility services, the inherently risky nature of e-scooters can also affect consumers' safety by impacting the number of crimes and crashes associated with their use. For example, e-scooters could result in more crimes, such as vehicle break-ins and crashes involving small vehicles. E-scooters could also impact consumer safety indirectly through their effects on mobility. We test these alternative possibilities in our research.

To address our research questions, we leverage 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, demographic data from the U.S. Census Bureau, major live events from the Chicago Park District, and consumer visits to retail locations from Safegraph. We use a propensity score matching (PSM) model and a difference-in-differences (DID) approach that compares the change in outcomes for census tracts in the e-scooter area with those of similar census tracts outside the e-scooter area before and after the entry of e-scooters. We also report the results for alternative identification strategies, including a time discontinuity analysis, a Synthetic DID analysis, and an analysis for alternative control groups farther from the e-scooter boundary 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 4.79% but decreases the number of bikeshare trips by 13.53%, which translates to $4.7 million higher revenues but also 510 metric ton more carbon emissions annually. Second, our results on consumer safety show that the entry of e-scooters increases crimes (e.g., vehicle break-ins) by 9.78% and crashes (e.g., bike accidents) by 56.23%, which further add to their economic costs each year. Third, the results from our heterogeneity analysis show that the effect of e-scooters on incumbent shared mobility is exacerbated for relatively older populations (i.e., positively moderated for ridesharing and negatively moderated for bikesharing) but attenuated for people of color (i.e., negatively moderated for ridesharing and positively moderated for bikesharing).[2] We also find that consumer safety worsens more in areas with a higher proportion of POC in terms of increased crashes. Finally, our mechanisms analysis reveals situations in which there may be a relative advantage (vs. disadvantage) of e-scooters based on the timing and type of usage. Specifically, the complementary relationship of e-scooters with ridesharing is strongest during non-peak traffic hours, for single riders, and for grocery and dining trips while the substitution relationship of e-scooters with bikesharing is strongest during weekdays for non-peak traffic hours and for longer-duration trips that e-scooters can best replace due to their high speed and reach. Finally, we find that crimes increase when they involve streets and vehicles, while crashes increase when they involve micromobility vehicles (e.g., bikes). We rule out other explanations, such as a supply-side effect of ridesharing and e-scooters' effects on consumer safety due to ridesharing.

Our research contributes to the literature on micromobility services and sharing economy. First, the emerging literature on micromobility in marketing has only focused on economic outcomes, such as housing price premiums due to the entry of shared bikes (Chu et al. 2020). Within micromobility, there are only two papers in marketing that examine e-scooters and both focus on their effects on restaurant visits and spending (Kim and Kannan 2023; Kim and McCarthy 2024). Prior research in marketing has not examined the impact of the entry of e-scooters on other key outcomes, such as consumers' use of other forms of shared mobility and their overall safety. We expand the focus of the micromobility literature by studying a rich set of outcomes related to consumers' mobility and safety. Second, research on the sharing economy has mostly focused on home- and ride-sharing platforms, such as Airbnb and Uber (e.g., Barron, Kung, and Proserpio 2021; Zervas, Proserpio, and Byers 2017) with little emphasis on micromobility. Most of this research evaluates the impact of sharing economy platforms on the same or similar industry (e.g., how Airbnb affects the hotel industry). With the exception of Zhang et al. (2022), there are not a lot of studies on important cross-platform effects in the sharing economy. Furthermore, with the exception of a handful

[2]Relatively older population refers to those above the median age of 34 years and people of color (POC) refers to majority non-white population.

of standalone studies on how ridesharing platforms impact motor vehicle accidents, the issue of consumer safety is not well understood in the sharing economy literature in marketing (Greenwood and Wattal 2017; Liu, Brynjolfsson, and Dowlatabadi 2021; Park et al. 2021). We contribute to the sharing economy literature by studying the cross-platform implications of a micromobility service (i.e., e-scooters) as well as its implications for consumer safety. 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 these important heterogeneities for relatively older populations and POC.

Our research has several implications for stakeholders, including shared mobility platforms and policymakers. First, our estimates suggest an economic benefit in terms of $4.7 million additional ridesharing revenues but also suggest higher environmental costs through emissions amounting to nearly 510 metric tons each year. Second, our results can inform shared mobility platforms for ridesharing and bikesharing about how to respond to the entry of a new micromobility service in terms of their service placement, fleet allocation, and customer engagement in a city. Third, our findings offer valuable insights for policymakers in the deployment and regulation of shared mobility services. The asymmetric impact of e-scooters on relatively older populations and people of color suggests that policies should be tailored to promote equitable access, particularly in neighborhoods with higher minority populations. Finally, the increase in crimes and crashes associated with e-scooter usage suggests that city planners and law and enforcement need to carefully design and enforce safety practices. This might include implementing better infrastructure, such as designated scooter lanes, or creating educational campaigns aimed at reducing reckless behavior among e-scooter users especially on the weekends when crime and crashes surge. Finally, our research highlights how e-scooter rollouts may fall short of accomplishing their broader goals of reducing car use via ridesharing as well as of enhancing equitable access to new forms of mobility to excluded populations.

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 to visualize the results, to benchmark the estimates, and to gain additional insights about the economic, societal, and environmental impact of e-scooters. Second, the app allows stakeholders to view custom reports focused on the outcomes and implications that are most relevant to them. Third, it documents additional analyses for a new set of variables (e.g., parking violations) 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. As an *explorer* app, it provides a user-friendly template and can be easily expanded to other cities with similar data as well.

RELATED LITERATURE AND CONCEPTUAL DEVELOPMENT

Our research relates to the emerging literature on micromobility services and the broader literature on the sharing economy. In this section, we first review the relevant literature and articulate our contribution. Based on the collective insights from this exercise, we then propose expected effects for our inquiry.

A summary of representative papers from the micromobility and the sharing economy literature along with our relative contribution appears in (Table 1).

Prior Literature: Key Insights and Limitations

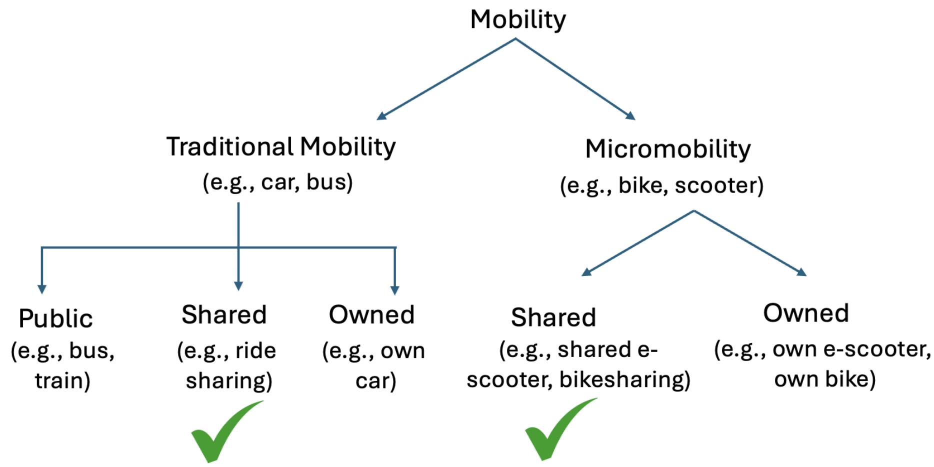
Micromobility services

Micromobility represents a group of small light-weight devices or mini-vehicles, such as bikes, e-bikes, and e-scooters (Oeschger, Carroll, and Caulfield 2020; Zarif, Pankratz, and Kelman 2019) unlike *mobility*, which represents a broad set of traditional transportation

Table 1: Summary of Selected Research and Our Contribution

Representative Paper	**Focus**	**E-scooter**	**Effect on Consumer Mobility**	**Effect on Consumer Safety/ Wellbeing**	**Cross-Platform Effects**	**Heterogeneity based on Neighborhood Demographics**	**Relevant Finding**
Micromobility Services							
Chu et al. (2020)	Effect of bikesharing on home prices	—	—	✓	—	—	Bike sharing reduces housing price premium by 29% per km away from a subway station, saving commuting costs
Kim and Kannan (2023)	Effect of e-scooter entry on restaurant visits	✓	—	—	—	—	E-scooter entry increases visits to restaurants, especially less popular ones
Kim and McCarthy (2024)	Effect of e-scooter entry on the food sector	✓	—	—	—	—	E-scooter entry increases spending on food and restaurants
Sharing Economy							
Babar and Burtch (2020)	Effect of ride-hailing on public transportation	—	✓	—	—	—	Ride-hailing lowers city bus usage and increases commuter rail usage
Barron, Kung, and Proserpio (2021)	Effect of home-sharing on house prices and rents	—	—	—	—	—	Airbnb increases home prices ans rents by inducing supply of short term and limiting long term rentals
Greenwood and Wattal (2017)	Effect of ride-hailing on motor vehicle fatalities	—	—	✓	—	—	Entry of Uber Services in California markets reduced alochol-related fatalities
Liu, Brynjolfsson, and Dowlatabadi (2021)	Effect of Uber on driver moral hazard and service quality	—	—	✓	—	—	Switch of drivers from taxi to Uber decreases moral hazard by reducing longer routing
Shin et al. (2023)	Effect of ride-hailing on restaurant quality	—	—	—	—	—	Presence of ridesharing services decreases restaurant quality by raising staff turnover
Zervas, Proserpio, and Byers (2017)	Effect of Airbnb's entry on hotel revenues	—	—	—	—	—	Airbnb lowers hotel revenues by 8%–10% especially for lower priced hotels
Zhang and Li (2021)	Effect of ride-hailing on consumption patterns	—	—	—	—	✓	Presence of ride-sharing services improves overall consumption
Zhang et al. (2022)	Effect of ride-sharing on home-sharing services	—	—	—	✓	✓	Uber/Lyft's exit in Austin led to a 14% decline in Airbnb occupancy
This paper (2024)	Effect of e-scooter entry on consumer mobility (i.e., ride- and bike-sharing) and safety (i.e., crime and crash)	✓	✓	✓	✓	✓	Entry of e-scooters increases ridesharing but decreases bikesharing use; it also increases crime and crashes in a city; the effects are heterogeneous by the age and racial composition of neighborhoods

Figure 1: Types of Mobility and Our Focus



Note: The green checkmarks denote the focus of our study, i.e., shared mobility.

vehicles, such as cars, buses, and trains (Abduljabbar, Liyanage, and Dia 2021). In recent years, both micromobility and mobility services have become accessible to users in shared formats without requiring ownership (see Figure 1). The emergence of shared formats of micromobility (e.g., Bird e-scooters, Ofo bikes) have led to a call for more research on their economic and societal impact. However, research on micromobility is still sparse and nascent.

An emerging body of research on micromobility services has examined the effects of bikesharing systems and shared e-scooters (Chu et al. 2020; Kim and Kannan 2023; Kim and McCarthy 2024). Early papers on micromobility have focused mainly on the effects of the entry of micromobility services on economic outcomes. Chu et al. (2020) examine the staggered entry of bikesharing platforms Ofo and Mobike in ten cities in China between 2015 and 2017. Using the spatial distribution of apartments that are at different distances to the same subway station, they show that bikesharing improves connectivity between homes and subway stations and attenuates price premiums for housing by 29% per kilometer. By capturing savings in the form of commuting costs, they outline some implications of bikesharing systems for consumer welfare. However, the focus of their research is not on e-scooters or on consumers' use of other mobility and their overall safety.

Two papers on micromobility that are directly relevant for our research on e-scooters are Kim and McCarthy (2024) and a working paper, Kim and Kannan (2023). Both papers study the effects of e-scooters on restaurants. Kim and McCarthy (2024) 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. Similarly, Kim and Kannan (2023) use foot traffic data to further show that e-scooters increase restaurant visits, particularly to less popular restaurants. Collectively, the results from these emerging papers provide evidence for higher food-related spending due to the launch of micromobility services. However, research so far is somewhat silent about the important economic and societal effects of e-scooters beyond the food sector, including those on consumers' other mobility choices (e.g., how e-scooters affect bikesharing usage) and consumers' safety (e.g., how e-scooters affect crimes and crashes in a city). Therefore, we focus on these under-studied outcomes in our research and quantify the effect of the entry of e-scooters in a city on consumers' use of incumbent shared mobility services and their safety.

As evident from Table 1 and our discussion so far, our research contributes to the micromobility literature in at least three ways. First, we expand the limited set of outcomes in prior research by examining consumers' use of incumbent shared mobility and their safety. It is important to quantify the impact of e-scooters beyond their economic value to the food sector to help cities and policymakers better evaluate and regulate them. Second, we examine the cross-platform effects of e-scooters for bikesharing and ridesharing systems in a city to better understand their potential spillovers for incumbent shared mobility systems. Third, we examine the heterogeneity in the effects of e-scooters based on neighborhood characteristics, such as the age and racial composition of its residents. Such a heterogeneity analysis is important for understanding asymmetries in the effects of e-scooters 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. Unlike extant research, we examine the effects of the entry of e-scooters *within* a city by leveraging the variation in the locations in which e-scooters were made available rather than across cities. 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).

Sharing economy

There is a rich and growing body of research on the sharing economy (e.g., Babar and Burtch 2020, Cramer and Krueger 2016, Dowling, Manchanda, and Spann 2021, Greenberg et al. 2023, Shin et al. 2023, Zervas, Proserpio, and Byers 2017). Much of this literature studies platforms for home-sharing (e.g., Airbnb) and ridesharing (e.g., Uber). Broadly, the sharing economy represents a technologically-enabled socioeconomic system for sharing of resources, such as homes and automobiles (Eckhardt et al. 2019).

Within the sharing economy, most extant marketing literature on mobility has focused on the effect of ridesharing services, such as Uber and Lyft on outcomes, such as restaurant quality and other consumption activity (Shin et al. 2023; Zhang and Li 2021) rather than their effects on other forms of mobility and on consumer safety. Shin et al. (2023) quantify the impact of Uber on restaurant quality through labor market changes. Zhang and Li (2021) shows increase in offline consumption activity after the entry of ride-hailing services in major metros and show that the effects are stronger for low-income groups.

Our research also draws from the work on demand interactions between shared mobility and shared home services, showing how Uber/Lyft's exit reduced the hotel occupancy rates for Airbnb in Austin (Zhang et al. 2022). However, evidence of such cross-overs is limited and most sharing economy research tends to examine outcomes within the same industry or sector as the focal intervention (e.g., Li and Srinivasan 2019; Zervas, Proserpio, and Byers 2017). Similarly, there is little emphasis on how one type of shared mobility platform impacts other forms of mobility for consumers. In one exception, Babar and Burtch (2020) document how the entry of ride-hailing platforms in U.S. cities impacts other mobility by reducing city bus and increasing commuter rail usage. However, the focus of this research is not on e-scooters or on the implications for other shared platforms and consumers' safety. Similarly, other studies have independently documented how Uber's presence in a city impacts alcohol-related car crashes and drivers' tendency to take longer-than-optimal routes (Greenwood and Wattal 2017; Liu, Brynjolfsson, and Dowlatabadi 2021). However, these studies do not focus on mobility choices or cross-overs with other shared platforms.

As evident from Table 1 and our discussion so far, our research contributes to the sharing economy literature in at least three ways. First, we examine a rich set of outcomes related to consumers' use of incumbent shared mobility and consumer safety; these outcomes, though important, are less understood in the sharing economy literature and to our knowledge, have not been studied in a single framework. Second, we examine cross-platform effects by studying how shared e-scooters impact other platforms, such as ridesharing and bikesharing; with the exception of Zhang et al. (2022), there are not a lot of studies on important demand interactions between various shared platforms. Finally, we explore heterogeneity by neighborhood types and reveal important asymmetries in the impact of e-scooters, adding to the literature that documents income-based inequities in the consumption-related benefits of ridesharing services (Zhang and Li 2021). 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 incumbent shared mobility and consumer safety within a city, suggesting important asymmetries by the type of neighborhood.

In the rest of this Section, we derive predictions for the impact of entry of new micromobility service (i.e., e-scooters) on incumbent shared mobility services and consumer safety.

Effects of New Micromobility Service (E-scooters) on Incumbent Shared Mobility

The entry of e-scooters, a new form of shared micromobility, could shift the demand for existing forms of shared mobility in a city (Zhang et al. 2022). There could be two potential effects on incumbent shared mobility when e-scooters enter: A substitution effect (i.e., the entry of e-scooters could lead to some users switching away from other mobility services in favor of using the e-scooters) vs. a complementary effect (i.e., the entry of e-scooters could lead to some users to using other mobility services in addition to e-scooters). If the substitution effect dominates, the existing shared mobility services will decrease in usage. However, if the complementary effect dominates, the existing shared mobility services will increase in usage. Next, we discuss the nature of these potential effects, depending on the relative characteristics and context of use of each service (see Table 2).

Table 2: Relative Characteristics of the Types of Mobility Services in Our Framework

	E-scooters	**Ridesharing**	**Bikesharing**
Category	Micromobility	Traditional mobility	Micromobility
Speed	Moderate	Variable	Low-Moderate
Storage space	Low	High	Low-Moderate
Physical effort	Low-Moderate	Low	High
Multiple riders	No	Yes	No
Congestion effects	Low	High	Low-Moderate
Use under influence	No	Yes	No
Last mile reach	Yes	Yes	No

Notes: Speed of rideshare depends on traffic conditions. Use under influence refers to permissible use under alcohol or drug consumption. Last-mile reach is not a feature of docked bikesharing, which requires parking at designated stations. Dockless e-scooters can be dropped off anywhere.

Effect on Incumbent Traditional Mobility Service: Ridesharing

E-scooters as a new form of micromobility share few similarities with ridesharing. E-scooters belong to the micromobility category while ridesharing typically includes traditional mobility vehicles, such as cars. While e-scooters are ideal for short, solo trips during designated hours, ridesharing services can accommodate multiple riders for trips of any length at any time. E-scooters require some physical effort, offer limited carrying space, and cannot be used under the influence, unlike ridesharing. However, both services provide last mile reach.

How will the entry of e-scooters impact ridesharing? On the one hand, it is possible that some ridesharing trips may be substituted by e-scooters. Trips that are of similar length (e.g., short trips), those that are aligned with e-scooters' characteristics (e.g., single riders, low need for storage), and those during peak traffic hours (e.g., rush hours) could be substituted by e-scooters. Indeed, a key 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).

On the other hand, it is also possible that e-scooters will serve a complementary relationship with ridesharing. E-scooters could expand the overall demand for new trips. These new trips could be entirely or partially completed using rideshare. E-scooters tend to increase demand for restaurants and food-related consumption (Kim and McCarthy 2024). So, it is possible that some of this increase is met by rideshare services suited for such trips either one way or both way. The low overlap between the characteristics of e-scooters and ridesharing (e.g., different category, nature of trips, multiple riders, congestion effects) could result in e-scooters enhancing the need for rideshare services. For example, a user could ride an e-scooter alone to go and meet friends and then take an Uber together, or a user might prefer rideshare during non-peak traffic hours when it is faster than e-scooters. Finally, e-scooters could also facilitate functional activities, such as errands. For example, a user could take an e-scooter to a retail or grocery store to make purchases. However, given their lack of suitability for carrying shopping bags, it is likely that the shopper will use ridesharing. In the absence of e-scooters, it is possible that either such trips would not have taken place at all or would have been pursued through other means (e.g., own vehicle). Therefore, the entry of e-scooters could result in more trips using ridesharing services. For these reasons, we posit that the entry of a new micromobility service (i.e., e-scooters) will result in an increase in the incumbent mobility service (i.e., ridesharing) due to a dominant complementary effect.

Effect on Incumbent Micromobility Service: Bikesharing

E-scooters represent a new entrant in shared micromobility services and share several characteristics with bikesharing. Both e-scooters and bikesharing belong to the micromobility category of light-weight vehicles and have several overlapping characteristics as shown in Table 2. However, e-scooters also exhibit several distinct characteristics. First, e-scooters tend to be faster in speed compared with biking (Asensio et al. 2022). Second, e-scooters do not require much physical effort from the users. Third, e-scooters solve the last-mile problem by providing direct access to pick-up and drop-off points by virtue of being dockless, unlike docked bikes that have designated stations (Baek et al. 2021). Therefore, e-scooters offer several additional features compared with bikesharing.

How will the entry of e-scooters impact bikesharing? On the one hand, it is possible that e-scooters will replace bikesharing trips due to the overlapping characteristics between the two (Abduljabbar, Liyanage, and Dia 2021). Given that bikes require more physical effort, 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). Such a substitution effect is likely when physical effort is not desired (e.g., when bikes are used for commute or errands, rather than for fitness or recreation) and when e-scooters offer a relative advantage, such as speed (e.g., longer trips will take more time on bikes).

On the other hand, it is also possible that e-scooters will result in an increase in bikesharing trips if they are used as a complement. E-scooters can facilitate getting riders to docked bike stations, which will in turn, increase their bike usage. However, this possibility is less likely since both e-scooters and bikesharing are suited for short trips. So if a user decides to use an e-scooter, they will likely do so to complete their entire trip rather than switch to a bike at a docked bike station. For these reasons, we posit that the entry of a new micromobility service (i.e., e-scooters) will result in a decrease in the incumbent micromobility service (i.e., bikesharing) due to a dominant substitution effect.

Overall, we expect that e-scooters will increase rideshare trips but decrease bikeshare trips due to their distinct vs. overlapping features, depending on the timing and type of usage (see Section on Potential Explanation: Timing and Type of Usage).

Effects of New Micromobility Service (E-scooters) on Consumer Safety

E-scooters can impact consumers' material and physical safety by impacting crimes and crashes due to their inherent risky nature (Pham 2021). Survey-based research has shown that consumers, particularly women, rank the perceived safety of e-scooters to be low (Sanders, Branion-Calles, and Nelson 2020). In the marketing literature, 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 or material safety (i.e., minimizing economic insecurity), and information safety (i.e., sense of confidence in access to the right information). We propose that consumers' material and physical safety are most likely to be impacted by e-scooters.

Material safety of consumers could be threatened by the entry of e-scooters through an increase in crime. It is possible that e-scooters 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). These types of crimes will likely increase during non-peak traffic hours when e-scooter can quickly speed away. 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. However, such effects are unlikely to materialize in the short-term.

Physical safety of consumers could be threatened by the entry of e-scooters through an increase in risk of physical injury through crashes. Physical safety, though at the base of Maslow's need hierarchy, is an important priority for marketers (Chen et al. 2024; Greenwood and Wattal 2017). Given the high speeds of e-scooters, reckless rider behavior, 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). These types of crashes will likely increase during non-peak traffic hours when e-scooter can be driven at greater speed and potentially on the weekend when riders may be engaged in reckless use.

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.[3]

Moderating Effect of Neighborhood Demographics

The main effects of the entry of e-scooters on incumbent shared mobility and consumer safety could vary depending on the type of neighborhood based on the age and racial composition of its residents. Most prior research examining diversity, equity, and inclusion (DEI) concerns in marketing has focused on either documenting bias and discrimination in different industries or on how pricing policies differentially affect minorities (e.g., Moshary, Tuchman, and Vajravelu 2023; Ozturk, He, and Chintagunta 2023, Wang et al. 2022, Zhang et al. 2021). Minorities are less likely to adopt new innovations (e.g., Wilson 2020). Furthermore, relatively older people may be less likely to use e-scooters compared to using traditional forms of transportation. POC may be hesitant to be exposed during e-scooter ride (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). 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 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

[3] It is also possible that e-scooter's effects on consumer safety are indirectly mediated through their impact on incumbent shared mobility (e.g., Greenwood and Wattal 2017; Park et al. 2021; Weber 2019). We test this possibility in our section on Ruling Out Alternative Explanations: Ridesharing's Effect on Consumer Safety.

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., incumbent shared mobility 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 census tract-level demographic data for each census tract in our data. Third, we collect data on major live events from the Chicago Park District. Finally, we collect data on consumer visits to retail locations from Safegraph, a company that records the global positioning system (GPS) data based on mobile pings at various locations visited by consumers. 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 incumbent shared mobility (i.e., rideshare and bikeshare trips) 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.[4]

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 at least one incident of such crimes and crashes respectively.

Next, we collect demographic information at the census tract level from the U.S. Census Bureau, Safegraph, the Chicago Department of Transportation, and the Chicago Park District. The demographic data include the mean household income, total population, young population (i.e., under the median age of 34 years old), number of people classified as non-white or POC, the availability of public transportation (e.g., bus stops), parking violation tickets, and the number of retail visits as well as major events in each census tract in Chicago.

In addition to the data on our key outcomes and demographics, we also collect data for our mechanisms analysis. Specifically, we collect additional data on rideshare and bikeshare

[4]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 C.20, we also report the results for long trips.

trips, including the day and time of the trips. For rideshare trips, we are also able to access the geo-coordinates of the start and end destination for a subset of trips. Finally, we collect data on other types of crimes (e.g., gun violence) and crash (e.g., vehicle collisions) to understand the mechanisms underlying the effects of e-scooters on crimes and crashes.

Summary Statistics

The summary statistics for our data appear in Table 3. On average, there are 392 rideshare trips and 74 bikeshare trips while there are 1.31 crimes and 0.06 crashes in a week in a census tract in our data period. The average household income in a census tract is $65,209.72 per annum. The average population is 3,470.91, the average number of young population below the age of 34 years is 1,764.59 and the average number of POC is 1,717.20. In terms of availability of public transportation, there are 13.54 bus and taxi stands on average in a census tract. The number of parking tickets due to violation of parking rules in a census tract is 8.58 on average each week and can indicate potential parking and congestion issues in those areas. Finally, there are 6.08 retail visits and 2.83 visits to tourism-related sites reported in the Safegraph data for each census tract-week in our analysis. We use these demographics to match and compare the treatment and control areas in our empirical analysis.

EMPIRICAL STRATEGY

Our goal is to examine how e-scooters impact a rich set of economic and societal outcomes, including incumbent shared mobility services (i.e., rideshare and bikeshare) and consumer safety (i.e., crimes and crashes). 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

Table 3: Variable Description and Summary Statistics

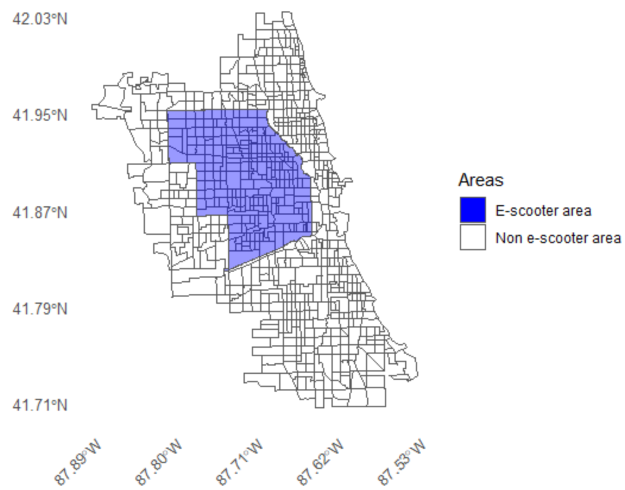
Variable	Description	Mean	Std Dev
Outcome: Incumbent Shared Mobility			
Rideshare	Weekly number of short rideshare trips of under two miles at the census tract level	392.10	1,525.21
Bikeshare	Weekly number of bideshare trips at the census tract level	73.90	137.26
Outcome: Consumer Safety			
Crime	Weekly 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
Other Variables			
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
Income	Annual average household income ($) in a census tract	65,209.72	36,951.91
Population	Total population in a census tract	3,470.91	1,761.18
Young population	Total population below 34 years old in a census tract	1,764.59	950.95
POC	Total population of people of color in a census tract	1,717.20	1,254.53
Public transport	Number of bus/taxi stops at the census tract level	13.54	8.37
Parking tickets	Number of parking tickets at the census tract level	8.58	25.88
Retail visits	Number of visits to retailers categorized as restaurant and retail stores at the census tract level	6.05	6.88
Tourism	Number of visits to museums, historical sites, and similar institutions at the census tract level	2.83	1.42

Notes: Outcome variables are at the census tract-week level before and after the entry of e-scooters for the 866 pre-matched census tracts over 41 weeks of the data. The demographics are averaged over the census tracts for which they are available in the 2010 census. POC = People of color.

(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).[5] Figure 2 shows a map of the treatment and control regions.

[5] The results are robust to alternative control groups farther from the e-scooter boundary and for alternative

Figure 2: E-scooter Area in Chicago



Propensity-Score Matched Difference-in-Differences Model

To quantify the effect of the entry of e-scooters, our main empirical approach relies on the following difference-in-differences model with two-way fixed effects (TWFE):

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

Where Y_{it} refers to the outcome variable Y in the week t for a census tract i. *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 census tract 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

identification strategies. See Sections Potential Spillover to Control Areas and Alternative Identification Strategies. We exclude the Chicago airport and forest preserve as these areas are idiosyncratic in their characteristics.

structure, which comprises observations across different census tracts 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 common time effects. Therefore, this model helps address potential confounding factors. Furthermore, 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 shared platforms 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 2024). 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, to ensure that the comparability of the treatment and control groups, we employ propensity score matching design with our DID estimator.[6]

We 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 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, income, population, young population, POC, public transportation, parking tickets, retail visits, and tourism in that area. Next, we calculate the propensity score for each of the 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 a census tract, $Escooter$ is the treatment i.e., the entry of

[6]We report the results of the unmatched DID analysis in Web Appendix Table A.1.

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 each of the pre-entry weeks, income, population, young population, POC, public transportation, parking tickets, retail visits, and tourism).

Finally, we match the census tracts for each outcome variable in the e-scooter and non e-scooter area based on the nearest neighbor matching without replacement by minimizing the difference in propensity scores:

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

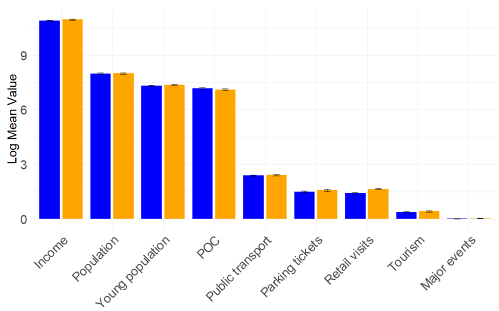
where $\widehat{p}$ is the propensity score, k refers to units in the e-scooter area, and j refers to units in the non e-scooter area. For each outcome variable, we repeat the matching process. We use the logarithmic transformation of the demographics used for matching because the past values of the outcome variables are relatively small and logarithmic transformation can keep a similar scale and ensure the stability in estimation. We report the balance of matching variables in our data pre- and post- matching in Web Appendix Tables B.1-B.4 to verify the quality of matches. These Tables show that after matching, the observed covariates of two groups look very similar.

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 provide additional analyses to address the SUTVA concerns including alternative control groups farther away from the e-scooter boundary. In the Section Alternative Identification Strategies, we also report our main results for shorter windows of time, using a Synthetic DID model, and for subsamples with high (vs. low) presence of e-scooters.

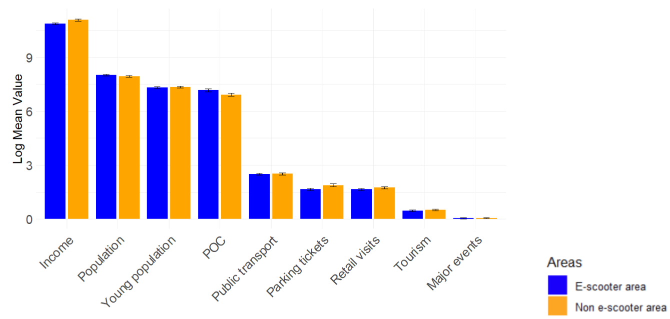
Endogeneity and Self-selection

In this Section, we report several important checks to verify that our main DID and matching approach is valid for quantifying the impact of e-scooters on outcomes of interest. First, we verified that the e-scooter area was similar to the matched non e-scooter area (see Figure 3). The Figure shows that the census tracts in the treatment and control areas are similar in their observed characteristics, (e.g., average income, population, young population, POC, public transportation).

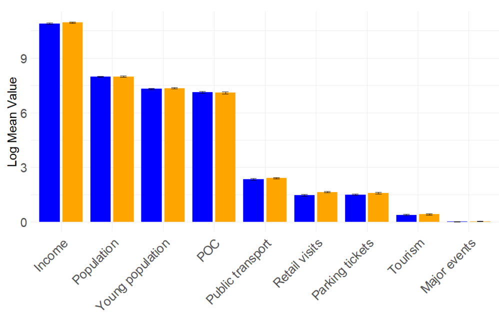
Figure 3: Comparison of Demographic Characteristics between the Treatment and Control Areas



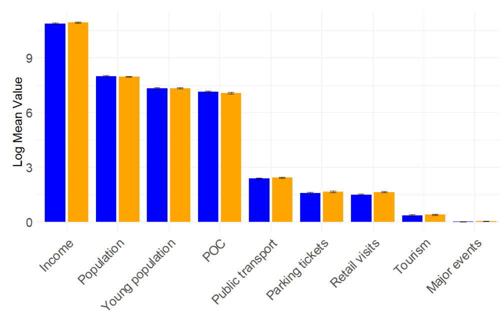
(a) Rideshare



(b) Bikeshare



(c) Crime

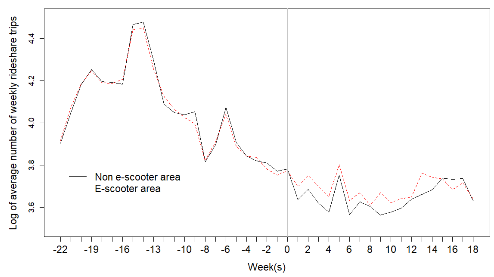


(d) Crash

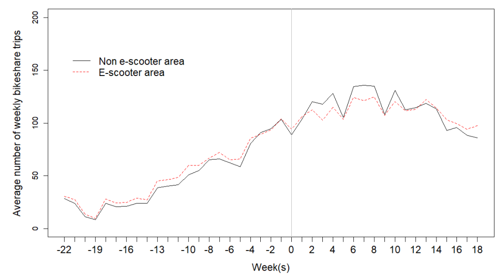
Notes: E-scooter area denotes the area in which e-scooters were allowed; non e-scooter area denotes the matched area in which e-scooters were not allowed. The details of matching for each outcome are reported in Web Appendix B. Population is the number of inhabitants; young population is the number of inhabitants under 34 years old; POC is the number of inhabitants of people of color.

Second, we verified that the pre-period trends for our outcome variables are parallel (see Figure 4). The pre-period trends of the four outcome variables in the e-scooter and non e-scooter areas appear similar. We also report the treatment effects for the pre- and postentry weeks over time in Web Appendix Figures E.1-E.4 as a test of parallel trends.

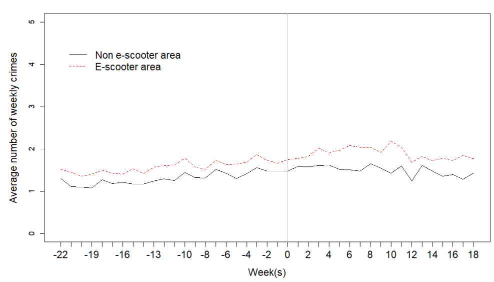
Figure 4: Pre- and Post- Period Trends of Incumbent Shared Mobility and Consumer Safety in the Treatment and Control Areas



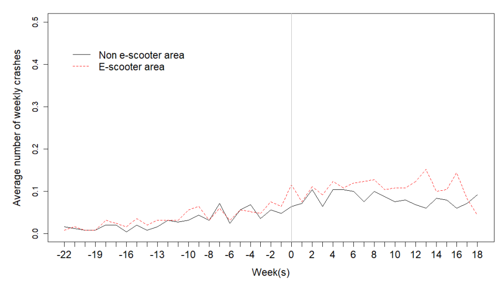
(a) Rideshare



(b) Bikeshare



(c) Crime



(d) Crash

Notes: E-scooter area denotes the area in which e-scooters were allowed; non e-scooter area denotes the area in which e-scooters were not allowed. Rideshare plot is scaled to logged form.

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 ($p > 0.10$). In case of rideshare, we do not find evidence of a growing trend in our data period. To account for any potential time-varying factors over the 41-week period in our data, we also report several analyses in the Robustness Checks Section, including a time discontinuity analysis for a shorter time window (Auffhammer and Kellogg 2011; Hausman and Rapson 2018), an alternative regression specification with linear and quadratic time trends, and alternative identification strategies, such as a Synthetic DID approach and alternative control groups to address spillover concerns (Arkhangelsky et al. 2021).

Fourth, it is possible that e-scooters are launched in higher population areas, which could be correlated with higher shared mobility 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.

Fifth, as reported earlier, we verified the quality of our propensity score matching analyses by inspecting the pre- and post- matching balance for each matching covariate and found them to be similar after matching (Web Appendix Tables B.1-B.4). Finally, we verified that the entry of e-scooters could not be pre-empted in advance by stakeholders (Ergin, Gümüş, and Yang 2022); it was not announced until close to the rollout in May.

RESULTS

The results from the DID model with propensity score matching are presented in Table 4.

We first discuss the results for the effect of e-scooters on incumbent shared mobility services. The results in Table 4 show that there is a significant increase in the number of weekly rideshare trips (α_1 = 17.679, 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 = -6.611, p $<$ 0.05). These effects translate to a 4.79% increase in rideshare trips and a 13.53% decrease in bikeshare trips 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 (α_1 = 0.128, p $<$ 0.01) and crashes (α_1 = 0.018, p $<$ 0.05) following the deployment of e-scooters. These effects translate to a 9.78% increase in the number of crimes and a 56.23% increase in the number of crashes compared to their pre-treatment levels in the non e-scooter area.

Overall, the results indicate that while the entry of e-scooters contributes positively to rideshare, it negatively affects bikeshare and increases crimes and crashes.

Table 4: DID Model Results with Propensity Score Matching

	Shared mobility		Consumer safety	
Variable	Rideshare	Bikeshare	Crime	Crash
E-Scooter × Post entry (DID)	17.679***	-6.611**	0.128***	0.018**
	(4.674)	(2.956)	(0.038)	(0.008)
Week FE	Yes	Yes	Yes	Yes
Census tract FE	Yes	Yes	Yes	Yes
N	21,566	8,528	21,484	20,582
Adj. R^2	0.984	0.770	0.519	0.101
Effect size	4.79%	-13.53%	9.78%	56.23%

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 for the matched sample.

Heterogeneity by Age and Race

Our main analyses show that the entry of e-scooters positively impacts ridesharing, but it adversely impacts bikesharing and consumer safety. We next investigate the heterogeneity in the effects based on the age and racial composition of a neighborhood, given the emphasis among cities to view e-scooters as a way to improve equitable access and opportunity.[7]

To examine the heterogeneity in the effects, we re-estimate our main regression with additional covariates that capture the interactions between the DID treatment effect (i.e., *E-Scooter* x *Post entry*) and each of our two moderating variables of interest: the number of older population (i.e., above 34 years) and the number of people of color. We also include the main effects and two-way interaction terms of the moderating variables to estimate the model. Table 5 reports the results.

The results in Table 5 indicate several interesting patterns. First, we find that the effects of the entry of e-scooters are positively moderated for rideshare trips (31.370, p < 0.01) and negatively moderated for bikeshare trips (-34.998, p < 0.01) among neighborhoods with

[7]We also report an analysis by socio-economic status (i.e., income) in Web Appendix Table D.3. We do not include income and race in the same model due to collinearity concerns.

Table 5: DID Model Results of the Entry of E-Scooters for Heterogeneity by Race and Age

	Shared mobility		Consumer safety	
Variable	Rideshare	Bikeshare	Crime	Crash
DID	-127.798*	14.182	0.976**	-0.010
	(75.898)	(42.165)	(0.472)	(0.093)
DID × Log(Older)	31.370***	-34.998***	-0.086	-0.018
	(12.118)	(7.070)	(0.077)	(0.016)
DID × Log(POC)	-11.209**	32.358***	-0.031	0.023**
	(4.420)	(3.710)	(0.059)	(0.011)
Week FE	Yes	Yes	Yes	Yes
Census tract FE	Yes	Yes	Yes	Yes
N	21,566	8,528	21,484	20,582
Adj. R^2	0.984	0.787	0.520	0.102

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 for the matched sample. We also include the main effects and two-way interaction terms of the moderating variables with each term (i.e., *E-scooter* and *Post entry*) but do not report them to save space.

higher older populations. We also find that the effects of the entry of e-scooters are negatively moderated for rideshare trips (-11.209, $p < 0.05$) among neighborhoods with a higher number of POC but positively moderated for bikeshare trips (32.358, $p < 0.01$). Second, we also find a significant interaction between the treatment effect and high POC neighborhoods for crashes. The effect of e-scooters on crashes is more positive in neighborhoods with a higher proportion of POC (0.028, $p < 0.05$) indicating the worse societal impact of e-scooters for these populations. 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 EXPLANATION: TIMING AND TYPE OF USAGE

Our main results show that the entry of e-scooters increases ridesharing but decreases bikesharing trips. Furthermore, it adversely impacts consumer safety. Importantly, the effects are heterogeneous based on the age and racial composition of a neighborhood. In this Section, we examine the potential mechanisms underlying these effects. Following our conceptual development, we explore the relative advantages and disadvantages of e-scooters, which we posit depend on the timing and type of occurrence of incumbent shared mobility trips (i.e., ridesharing and bikesharing) and consumer safety events (i.e., crimes and crashes).

First, our result that e-scooters boost ridesharing reveals a complementary relationship between e-scooters and ridesharing services. To understand the mechanism underlying this result, we examine the situations in which rideshare use can be augmented by e-scooters based on the unique characteristics of each service. Specifically, we analyze the effects of e-scooters on ridesharing services by day of week (i.e., weekday vs. weekend), by time of day (i.e., peak vs. non-peak traffic hours), by trip type (i.e., shared vs. single rider trip), and by trip purpose (i.e., destination).[8]

The results of our exploration of the effects on ridesharing appear in Table 6. This Table shows that while e-scooters increase rideshare trips for both weekdays and weekends, the increase is stronger in non-peak traffic hours (i.e., non-commute hours outside 7-9am and 5-7pm) and for rideshare rides with a solo rider only, rather than shared rides. These results suggest that e-scooter may be increasing rideshare more during non-peak traffic hours when there is less congestion faced by rideshare and for trips by a single rider. Figure 5 reports the increase in rideshare trips by the *purpose* of trip using the nearest place-of-interest (POI).[9] The top destinations are grocery, dining, and places of business. Therefore, riders may be

[8] We define the peak traffic hours as commute hours between 7-9am and 5-7pm based on Chicago traffic reports (e.g., https://www.tomtom.com/traffic-index/chicago-traffic/). In Web Appendix Tables D.1 and D.2, we also report the analysis of peak and non-peak traffic hour for each outcome by weekday and weekend.

[9] In Web Appendix Figure D.1, we also report these plots by day of week and time of day. In Web Appendix Table F.1, we describe the categories with examples. We identify the destination for a trip based on the nearest POI within 30 meters of the drop-off point of a rideshare trip for a random sample of 10,000 trips reported in Figure 5.

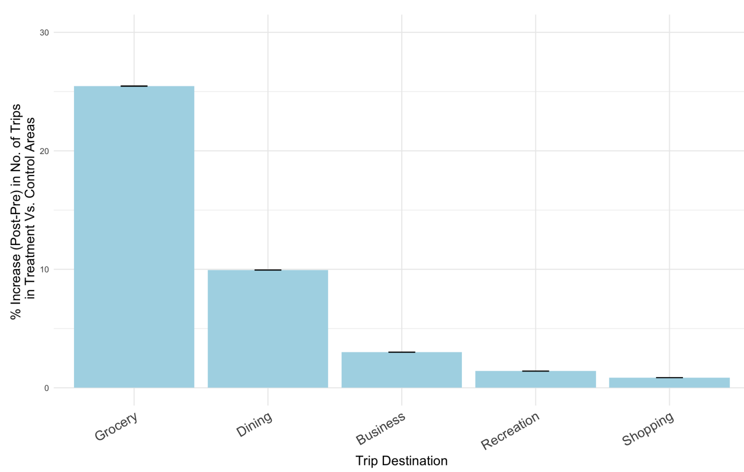
using rideshare for errands (e.g., trip to the grocery store), eating out (e.g., dining), etc.[10]

Table 6: DID Model Results for the Effect of E-scooters on Ridesharing by Timing and Type of Use

	Day of week		Time of day		Type of trip	
Variable	Weekday	Weekend	Peak	Non-peak	Shared	Single
E-Scooter × Post entry (DID)	12.157***	13.146***	6.693***	38.009***	1.155	20.236***
	(2.961)	(3.465)	(1.716)	(12.587)	(1.471)	(6.137)
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Census tract FE	Yes	Yes	Yes	Yes	Yes	Yes
N	21,074	15,703	20,992	15,908	16,236	15,662
Adj. R^2	0.981	0.977	0.970	0.989	0.844	0.988
Effect size	6.36%	4.82%	6.79%	9.08%	-	4.43%

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 for the matched sample. Single rideshare trip refers to one rider only.

Figure 5: Change in Percentage of Rideshare Trips by Trip Purpose



Second, our result that e-scooters decrease bikesharing trips reveals a substitution relationship between the two services. To better understand the mechanism, we examine the situations

[10] It is possible that e-scooters could replace a trip earlier planned using rideshare and result in a net decrease. However, our main results show an overall increase in rideshare. Similarly, the increase in rideshare could be supply-side driven, rather than demand-driven. In this case, we should see ridesharing generally becoming more available and popular during our data period. However, ridesharing generally trends downward in our data period both in the treatment and control group (see Web Appendix Figure A.1). Overall, our results support that e-scooters expand consumption and contribute to rideshare trips (e.g., Deng, Gan, and Hu 2021). For example, Web Appendix Table C.21 reports an increase in retail visits, consistent with increase in rideshare trips to these places in Figure 5.

in which e-scooters might replace bikesharing. The results are reported in Table 7. This Table shows that e-scooters decrease bikesharing trips primarily during weekdays rather than weekends. The decrease is more during non-peak traffic hours and for relatively longer bikesharing trips. One possible explanation is that e-scooters offer greater speed and convenience advantage over bikeshare by requiring less physical effort, which helps riders during weekdays, in non-commute peak hours, and for long trips more.

Table 7: DID Model Results for the Effect of E-scooters on Bikesharing by Timing and Type of Use

	Day of week		Time of day		Type of trip	
Variable	Weekday	Weekend	Peak	Non-peak	Long	Short
E-Scooter × Post entry (DID)	-14.041***	-2.555	-6.819***	-15.014***	-55.504***	3.018
	(2.883)	(1.917)	(1.610)	(3.313)	(6.662)	(2.661)
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Census tract FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4,264	4,182	3,772	5,330	1,558	5,576
Adj. R^2	0.790	0.779	0.799	0.773	0.648	0.825
Effect size	-25.91%	-	-20.29%	-28.24%	-127.37%	-

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 for the matched sample. Long bikeshare trips refer to longer than 2 miles.

Finally, the results for our mechanism analysis for consumer safety appear in Tables 8 and 9. Both for crimes and crashes, we find that the safety concerns become worse during the weekends and in non-peak traffic hours. Furthermore, the increase in crime comes from those involving streets (e.g., snatch-and-run) and vehicle (e.g., break-ins) rather than other types of crimes (e.g., home or store theft). The increase in crashes comes primarily from crashes involving bikes and micromobility vehicles.

Our mechanisms analyses show several key results. First, we find evidence for a complementary relationship of e-scooters with ridesharing, which is strongest during non-peak traffic hours, for single riders, and for grocery and dining purposes. Second, we find evidence for a substitution relationship of e-scooters with bikesharing, which is strongest during weekdays for non-peak traffic hours and for longer-duration trips that e-scooters may replace due to their high speed and reach. Finally, we find that crimes increase when involving streets and vehicles only and for crashes involving micromobility (e.g., bikes).[11]

Table 8: DID Model Results for the Effect of E-scooters on Crime by Timing and Type of Crime

	Day of week		Time of day		Type of crime		
Variable	Weekday	Weekend	Peak	Non-peak	Street	Vehicle	Other
E-Scooter × Post entry (DID)	0.041	0.078***	0.026*	0.111***	0.075**	0.046***	-0.034
	(0.028)	(0.025)	(0.015)	(0.034)	(0.036)	(0.012)	(0.060)
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census tract FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	21,484	21,484	21,484	21,484	21,484	21,484	21,484
Adj. R^2	0.373	0.354	0.168	0.486	0.577	0.125	0.822
Effect size	-	12.70%	11.16%	9.87%	6.13%	38.26%	-

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 for matched sample. Street- and vehicle- related crimes include vehicle break-ins, or snatch-and-run incidents; other crimes relate to home or store theft, gun violence, and killings.

Table 9: DID Model Results for the Effect of E-scooters on Crash by Timing and Type of Crash

	Day of week		Time of day		Type of crash		
Variable	Weekday	Weekend	Peak	Non-peak	Small vehicle	Personal injury	Motor vehicle
E-Scooter × Post entry (DID)	0.009	0.006*	0.007	0.013**	0.018**	0.003	-0.063
	(0.006)	(0.004)	(0.004)	(0.006)	(0.008)	(0.012)	(0.127)
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census tract FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	20,582	20,582	20,582	20,582	20,582	20,582	20,582
Adj. R^2	0.083	0.024	0.048	0.058	0.101	0.165	0.672
Effect size	-	98.82%	-	66.42%	56.23%	-	-

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 for the matched sample. Personal injury and motor vehicle crashes refer to those involving drivers, passengers, or motor vehicle accidents rather than bike- or scooter- crashes comprising small vehicle crashes.

[11] We also rule out an effect on consumer safety due to mediation by rideshare. See Section on Ruling Out Alternative Explanations: Ridesharing's Effect on Consumer Safety for details.

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 explanations, alternative matching and model specifications, placebo tests, and outlier observations.

Potential Spillover to Control Areas

In our research design, a possible threat to our identification strategy could be the potential for spillovers between the treatment and control census tracts. Specifically, since our research leverages within-city variation in the entry of e-scooters, there could be potential effects of the treatment in the control regions. We address these potential concerns in several ways. First, we report face validity checks from the institutional setting and the raw data to examine whether such spillovers are present in our setting and to what degree. The geo-fencing technology that governs e-scooter usage 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 still possible that the mere entry of e-scooters affects outcomes in the control region if there is some substitution in traffic between control and treated areas and we see a dip in traffic immediately after the e-scooters enter. We visually inspect the trends for rideshare and bikeshare trips in Figure A.1 and report the results of t-tests comparing the pre- and post- period outcomes in the control areas in the immediate time period after the treatment. The number of rideshare trips are not significantly different in the control region ($p > 0.10$) while the number of bikeshare trips are higher and marginally significant ($p = 0.07$) in the four weeks before and after the entry of e-scooters. Overall, we do not observe a large change that is unique to the control areas. Such a change, if present, could violate the stable unit of treatment value assumption (SUTVA) i.e., that there should be no spillover of treatment to the control group.

Despite these face validity checks, there could be some concern for spillovers very close to the boundary of the e-scooter area that separates the treatment and control groups. To address these potential concerns, we conducted three additional analyses. First, we checked the extent of bikesharing trips that cross-over between the two areas given the marginally significant increase in such trips in the control area. We find 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. Such an analysis cannot completely address the possibility that e-scooter users could still walk over and cross the two areas, especially if within a close distance from the e-scooter boundary. However, this possibility is less likely for farther away census tracts. Second, to analyze the data for census tracts farther away, we repeat our analysis by excluding a buffer area around the e-scooter border and repeating the propensity score matching and DID models. 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 or outside this distance of the e-scooter boundary. Web Appendix Table C.1 shows the results of the robustness check. We find that the results are consistent with those of the main results even after dropping the buffer regions near the boundary of the e-scooter area. Finally, we also repeat our analysis using an alternative control group of census tracts farther away from the e-scooter boundary but keeping all the treated census tracts. Specifically, we use only those census tracts as control groups that are at least two miles away from the e-scooter boundary.[12] We report the results for the alternative control group in Web Appendix Table C.2 and find similar results as the main analysis. Across our various analyses, we verify the robustness of our results to concerns for potential SUTVA violations.

[12]The distance threshold is based on typical e-scooter trip distances and sample size constraints. If we filter our control groups using a larger distance threshold, the eligible sample size of census tracts does not allow for quality matches.

Alternative Identification Strategies

Our main empirical approach uses propensity score matching and a DID model. Although our checks show that the matched treatment and control groups are comparable and have parallel pre-period trends, we test the robustness of our results to alternative identification strategies. First, we use a regression discontinuity in time analysis around a shorter window of time 12 weeks pre- and post- the entry of the e-scooters (Hausman and Rapson 2018). The goal of this analysis is to account for the possibility that other events or changes over longer periods could be driving our estimates. We report the results of this analysis in Web Appendix Table C.3 and Table C.4. We find results that are largely consistent with those from the main model.[13] Second, we use the Synthetic Difference-In-Differences (Synthetic DID) methodology (Arkhangelsky et al. 2021) to allow for a more flexible approach for selecting the control group as a convex combination of control units based on assigned weighs. We report the results for this approach in Web Appendix Table C.5. We find results that are qualitatively similar to those from the main model with the exception of bikeshare that has a negative effect consistent with the main model, but is statistically insignificant. Finally, we report additional analyses for high- and low- treatment intensity areas based on higher- and lower- than median number of e-scooter trips in a census tract. Such an analysis is in the spirit of a complier average causal effect (CACE) where high-intensity areas are analogous to compliers. We report the results for high and low intensity areas in Web Appendix Tables C.6 and C.7. As expected, the high-intensity areas with more e-scooter trips generally have a larger magnitude and significance of effects relative to low-intensity areas.

Ruling Out Alternative Explanations: Major Events

While a regression discontinuity analysis in time mitigates some concern for events over longer time periods driving our effects, we also directly test for this possibility. Specifically,

[13]In Web Appendix E, we also report the results for shorter post periods of 4, 8, 12, and 16 weeks post the treatment as well as plots of dynamic treatment effects by time.

it is possible that our effects are driven by live events in the city rather than the entry of e-scooters. Such an explanation may be likely since users may go to these events using e-scooters to avoid parking hassles and congestion. To test for this explanation, we collected additional data on all major events in Chicago in 2019. Our data comprise of 812 events categorized by the city of Chicago as a festival or performance or any event with over 12,000 expected guests. Examples of such events include the Taste of River North festival, Bud Biliken Parade, Riot Fest, and Bank of America Marathon. To test the robustness of our results to such events, we perform several additional analyses. First, we examine the correlation between these events and the e-scooter area to see if such events are more likely to take place in the e-scooter area. We find that the correlation is low at 0.005. Second, we exclude the data on weeks in which such a major event occurred and re-estimate the DID model. The results appear in Web Appendix Tables C.8 and C.9 for analyses dropping major events in both treated and control regions as well as those dropping major events only in the treated area. We find similar results even after excluding major event weeks. Next, we identify the first major event in the e-scooter area and analyze the effects for the time period between the entry of the e-scooters and the date of that event. We report the results in Web Appendix Table C.10 and find similar results. Finally, we also test the robustness of our findings to the inclusion of separate linear and quadratic time trends for treated and control groups to account for time-varying unobservables that change gradually. The results appear in Web Appendix Table C.11 and show consistent effects as the main analysis. We also find qualitatively similar effects when we use shorter time windows of 12 weeks for a time discontinuity-style analysis (see Web Appendix Tables C.3 and C.4).

Ruling Out Alternative Explanations: Ridesharing's Effect on Consumer Safety

In addition to the direct effect of e-scooters on consumer safety (i.e., crimes and crashes), there could be potential indirect effects on consumer safety through e-scooter's effects on ridesharing. Extant literature on the sharing economy shows that Uber's presence in a city impacts alcohol-related car crashes (Greenwood and Wattal 2017). Similarly, ridesharing services can also impact certain types of crimes, e.g., assault (Park et al. 2021; Weber 2019). Based on this logic, we tested the mediation of e-scooters' impact on crimes and crashes by ridesharing (e.g., Barron, Kung, and Proserpio 2020; Lu, Dinner, and Grewal 2023). We tested three linkages. First, we need to test that e-scooters are correlated with the outcome (i.e., consumer safety). Second, e-scooters should be correlated with the mediating variable (ridesharing). Third, ridesharing, the proposed mediator, should impact consumer safety. Finally, for full mediation, we should find that the effect of e-scooters on consumer safety is no longer statistically significant when controlling for ridesharing. In the absence of the last condition, then mediation is partial. We estimated a mediation model with 1,000 bootstrap samples to investigate the potential indirect effects of e-scooters on consumer safety (i.e., crimes and crashes) through their impact on ridesharing. Our results indicate no significant evidence of mediation of crime by ridesharing, as the proportion mediated is -0.01 (95% CI: [-0.07, 0.03], $p = 0.6$). However, we find some evidence of a negative mediation of crashes by rideshare, as the proportion mediated is -0.33 (95% CI: [-1.49, -0.08], $p = 0.008$), indicating a reducing effect. This is consistent with the prior research on how Uber's presence in a city impacts car crashes (Greenwood and Wattal 2017; Liu, Brynjolfsson, and Dowlatabadi 2021). Nonetheless, the main effect of e-scooters on crashes remains positive and significant, consistent with the main analysis.

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). In caliper matching, we limit the absolute distance, $\|\widehat{p}_i - \widehat{p}_j\|$, between the propensity scores of a census tract 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. Web Appendix Tables C.12 and C.13 show that the results of these matching methods are consistent with those from 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 crimes, and the number of crashes. The results of the Poisson models for these outcome variables appear in Web Appendix Table C.14. This Table shows that the results for each of the outcome are generally consistent with our main model with the exception of the coefficient for the number of crashes, which isinsignificant 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. We carry out several such tests. First, we collect data on our key outcomes for 2018.[14] Since the e-scooters did not enter until 2019, we should not find any effects for 2018 over the same 41 weeks. To test this, we estimated a similar DID regression model as our main model for the same treated and control census blocks over the same 23 and 18 weeks pre- and post- June 15, 2018. The results are reported in Web Appendix Table C.15. Indeed, we do not find significant effects under this placebo. Second, we carry out three additional tests in our 2019 main sample 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 C.16, C.17, and C.18 report the effects of these placebo checks. These results show that the effect of the entry of e-scooters is not significant for these placebo analyses for any of the outcomes ($p > 0.10$), assuring us that the results are not spurious.

[14]The data on bikeshare, crimes, and crashes are available for 2018. However, the rideshare data are not available prior to November 2018 so we could not include rideshare in the 2018 placebo test.

Outliers

The effects could be driven by outlier census tracts that have disproportionately more trips and safety concerns. To test if our main results are robust to outliers, we estimate our DID model after dropping census tracts 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 C.19. This table shows that the results without outliers are consistent with our main model.

Alternative Measures of Outcome Variables

Our main analysis quantifies the effect of the entry of e-scooters on the outcomes we theoretically expect to be impacted by e-scooters and that are not explored by extant research (e.g., incumbent shared mobility). However, it is possible that e-scooters will impact other outcomes, such as public transportation and consumers' retail visits. We report the results for these additional outcomes in Web Appendix C.20 and C.21. We find that consistent with the positive effect of e-scooters on rideshare, there is a positive and significant effect on public transportation (i.e., taxis). Similarly, we also find a positive and significant effect on retail visits in the e-scooter areas after the entry of e-scooters, boosting overall economic outcomes. These results are consistent with extant research on e-scooters in marketing (Kim and McCarthy 2024; Kim and Kannan 2023).

APP IMPLEMENTATION

Our research is accompanied by an interactive web interface for visualizing the key results and implications. Our research is relevant for several stakeholders, including consumers, shared mobility platforms, policymakers, and cities. To make our research more accessible to these audiences and to spark more research on micromobility and its complex impact on consumers and firms, we provide an interactive research app companion. The app also allows stakeholders to benchmark the economic, societal, and environmental impact of our estimates. Our research is well suited for an app companion both due to the richness of the economic and societal outcomes we study 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 app is available at https://e-scooter.shinyapps.io/e-scooter/. The screenshots from the app showing the main functionality appear in Web Appendix Figure G.1. 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 income, population, young population, people of color, public transport, parking tickets, retail visits, tourism, and major events in each census tract in Chicago.

In addition to the main features directly related to our research, the app also provides two advanced features. First, the additional results page in the app reports results for the effects on parking violation 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., city official). Once the user selects their role, they are shown the relevant results and research implications.

Overall, the app companion offers four key benefits. First, the app extends the contribution of the research by providing an interactive interface to visualize the results, to benchmark the estimates, and to gain additional insights about the economic, societal, and environmental impact of e-scooters. Second, the app allows stakeholders to view custom reports focused on the implications that are most relevant to them. Third, it documents additional analyses for a new set of variables (e.g., parking violations) not focal to the paper. Finally, it serves as a visualization tool to explore patterns in the data and generate new research questions.

CONCLUSION, IMPLICATIONS, AND LIMITATIONS

E-scooters, a new form of shared micromobility, are expanding rapidly and disrupting both traditional mobility services (e.g., ridesharing) and micromobility services (e.g., bikesharing). However, despite their potential benefits of expanded mobility, e-scooters can also result in negative societal effects. For example, e-scooters can threaten consumers' material and physical safety, which is closely related to their mobility and movement patterns in a city. In this research, we addressed three research questions: First, what is the impact of the entry of e-scooters in a city on incumbent shared mobility (i.e., rideshare and bikeshare trips) 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 timing and type of usage explain these effects? By examining the effects of e-scooters and their potential mechanisms, our research contributes to the emerging literature on micromobility services and the more established literature on the sharing economy.

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 (i.e., incumbent shared mobility and consumer safety).

First, our research expands the understanding of how micromobility systems influence other incumbent forms of mobility. So far, neither the micromobility nor the sharing economy literature has investigated this important effect. For example, the micromobility studies have primarily focused on its economic effects on food-related spending and housing prices (e.g., Chu et al. 2020; Kim and McCarthy 2024). Similarly, the sharing economy literature has at best considered how ridesharing impacts the utilization of city bus and commuter rail services in terms of their effect on other mobility options (Babar and Burtch 2020). While useful for our inquiry, these studies offer little insight about how shared micromobility systems might impact other systems within the sharing economy, the focus of our study.

Second, we expand the scope of both the micromobility and sharing economy literature by offering a deeper understanding of consumer safety outcomes resulting from new micromobility systems. With the exception of a handful of standalone studies on how ridesharing platforms impact motor vehicle accidents, the issue of consumer safety is not well understood in the sharing economy literature in marketing (Greenwood and Wattal 2017; Liu, Brynjolfsson, and Dowlatabadi 2021; Park et al. 2021). Our insights extend the knowledge of interactions between mobility systems and consumer safety beyond how ridesharing affects incidence of accidents and assaults.

Third, 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 the within-platform or same-industry implications of ride- and home-sharing platforms. We contribute to the sharing economy literature by studying the cross-platform implications of a micromobility service (i.e., e-scooters).

Fourth, we provide insights that are relevant from a societal and environmental perspective (Olsen, Slotegraaf, and Chandukala 2014; Zhang, Chintagunta, and Kalwani 2021). Our outcomes on consumer safety recognize a theme that is increasingly important for managers but less explored in the marketing literature (Berry et al. 2020). Similarly, 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 (Fu et al. 2023).

Finally, our research is uniquely inter-disciplinary and integrates the research in marketing with related work in transportation, energy, and urban economics. 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 rideshare trips contrary to expected effects (Asensio et al. 2022). We explain our counter-intuitive findings through a granular analysis of trip-level rideshare data, uncovering patterns and approaches that may be of interest within and beyond the marketing academic community, for instance, to transportation researchers (Oeschger, Carroll, and Caulfield 2020).

Our research inquiry and findings seek to theoretically advance the marketing literature. We uncover an important dual and asymmetric impact of e-scooters, a new micromobility innovation. In doing so, we highlight that technologies that generally appear to expand the local economy may have important unintended downsides. For example, while our effects translate to higher ridesharing revenues, they also imply higher economic and environmental costs more broadly. Some of the cost to consumers in the form of material and physical injury resulting from e-scooters could backfire for marketers and cities introducing these new technologies. Our research brings the complex economic and societal outcomes of new mobility innovations into the purview of marketing's impact on consumers, firms, societies, cities, and the environment.

Implications for Practice

Our research provides useful economic and environmental benchmarks for the effects of e-scooters along with several implications for practice.

Economic and environmental significance. Our analysis of the effect of the entry of e-scooters reveals an increase in the number of rideshare trips by 4.79%, a decrease in the number of bikeshare trips by 13.53%, and an increase in the number of crimes and crashes by 9.78% and 56.23% respectively. Our effects suggest an economic benefit for rideshare platforms coupled with both environmental costs through higher carbon emissions as well as economic costs in the form of managing additional crimes and crashes. In this Section, we provide a back-of-the-envelope calculation to quantify the real-world impact of our estimates.

First, we quantify the increase in revenues for rideshare platforms. While our main analysis estimates the increase in the number of trips, we also collected the data on the fare charged per trip. We report the estimates for the weekly revenues at the census-tract level in Web Appendix Table C.20. This Table shows that weekly revenue at the census-tract level increases by \$103.67 after the entry of e-scooters. Within our sample of 18 weeks and 866 census tracts, we can expect an increase in ridesharing revenues of \$1.6 million.[15] These short-term effects, if persistent, could translate to as much as \$4.7 million over a year.

Second, we quantify the environmental impact of e-scooters on carbon emissions through their impact on ridesharing and bikesharing. Our main results show that e-scooters increase the number of short rideshare trips by 17.679 per week in a census tract (see Table 4). An average trip is about 1.15 miles in our sample. Therefore, each week, rideshare miles traveled increase by about 20 miles (i.e., 17.679 x 1.15 miles for short trips). Furthermore, according to estimates from the Environmental Protection Agency (EPA), the average passenger vehicle emits approximately 400 grams of CO2 per mile.[16] Therefore, within our sample and for short rideshare trips alone, the effects will translate to 124,704,000 grams or 124.7 metric tons (i.e., 20 miles x 18 weeks x 866 census tracts x 400 grams).[17] Assuming these effects last over a year, we could expect increased emissions of about 360.26 metric tons in Chicago using similar back-of-the-envelope calculations. If we account for the increase in long trips for rideshare and taxis (see Web Appendix Table C.20), the additional emissions could amount to nearly 12 thousand metric tons (i.e., 16.28 + 72.46 trips x 7.5 miles for long trips x 52 weeks x 866 census tracts x 400 grams). Furthermore, increased carbon emissions can lead to higher healthcare and energy costs, infrastructure damage, and a broader economic impact not accounted for in our computations.

Finally, while our estimates of the environmental costs account for increased rideshare, we also find a substitution effect of e-scooters on bikeshare by about 6.611 trips each week (see Table 4). On average, the bikeshare trips in our data have a distance of 2.5 miles. Assuming e-scooters substitute these trips, we can also compute the environmental impact of substituting bikshare trips by e-scooters based on 202 grams of CO2 producted by e-scoorers

[15] Our back-of-the-envelope computation assumes that the effects last for 18 weeks, which seems reasonable based on the results of the dynamic effects on ridesharing reported in Web Appendix E. The effects over 18 weeks are computed as \$103.67 x 18 weeks x 866 census tracts.

[16] https://www.epa.gov/greenvehicles/greenhouse-gas-emissions-typical-passenger-vehicle

[17] 1 metric ton = 1,000,000 grams.

per passenger mile (Hollingsworth, Copeland, and Johnson 2019). E-scooters replacing bikes would result in an additional 150.61 metric tons, following our previous annual calculations. In total, the environmental impact of e-scooters appears to be in the range of 510 metric tons just from their effects on short rideshare and bikeshare (i.e., 360.26 and 150.61 respectively).

Other managerial implications. In addition to providing benchmarks for the economic and environmental impact of e-scooters, our research offers at least four additional managerial implications. First, our result that e-scooters have a complementary relationship with ridesharing but a substitution relationship with bikesharing reveal important spillovers across sharing economy platforms. These results can guide shared mobility platforms in their service placement and customer engagement efforts in response to the introduction of e-scooters in a city. Divvy bikesharing systems, for example, can plan their station locations and distribution in areas where e-scooters are less used and least likely to substitute bikesharing. Uber drivers can similarly pre-empt higher demand for short trips in areas with e-scooters and plan their locations and hours of service, expecting more demand from e-scooter locations.

Second, our research has important implications for public policy officials and cities introducing e-scooter programs to improve equity and access by suggesting that e-scooters have asymmetric effects for non-White and older populations. 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 among excluded populations.

Finally, the increase in crimes and crashes after the entry of e-scooters indicates the necessity for regulators to develop better infrastructure, such as dedicated scooter lanes, and implement stricter safety regulations. Our results show that crime and crashes surge more on the weekends once e-scooters enter. Firms, regulators and the non-profit sector can launch campaigns for reducing reckless behavior among e-scooter users, especially during weekends. Overall, our research suggests that the current e-scooter rollouts may not fully achieve their intended goals of reducing car usage or promoting equity, calling for more effective strategies.

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, our analysis relies on census tract-level data, which may not capture the full heterogeneity within neighborhoods. Variation in e-scooter usage and its impact at a more granular level, such as individual streets or blocks, could provide additional insights. Second, while we provide back-of-the-envelope calculations about e-scooters' environmental impact based on additional carbon emissions from ridesharing, we do not observe consumers' ownership or use of their own vehicles and cannot factor that into our estimates. If such data are available, research can further refine the estimates of additional carbon emissions. Third, 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 and other e-scooter pilot programs if such data are available. For example, the City of Chicago launched another pilot e-scooter program in 2020. If data are available, an analysis of other e-scooter programs can help generalize our findings. Fourth, 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 other important consumer characteristics, such as gender and consumption preferences (e.g., car ownership). Future research may be able to capture additional dimensions of heterogeneity 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, 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 or their usage by consumers through pricing, parking, or other targeted interventions.

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Web Appendix

How E-Scooters Impact Shared Mobility and Consumer Safety

Table of Contents

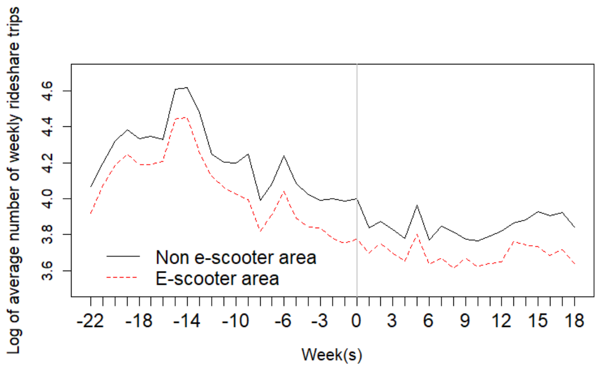
A Main analysis: Unmatched DID

Table A.1: DID Model Results

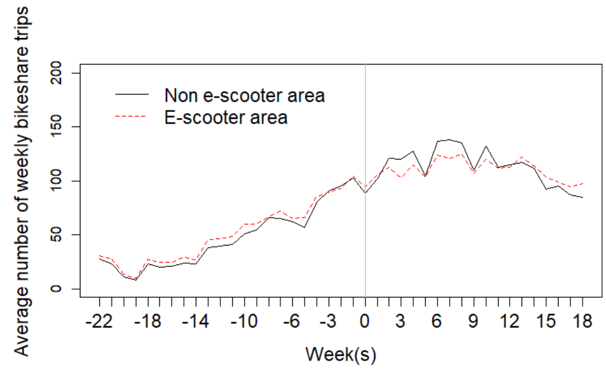
Variable	Shared mobility		Consumer safety	
	Rideshare	Bikeshare	Crime	Crash
E-Scooter × Post entry (DID)	28.580***	-6.094***	0.148***	0.017**
	(3.810)	(2.679)	(0.034)	(0.007)
Week FE	Yes	Yes	Yes	Yes
Census tract FE	Yes	Yes	Yes	Yes
N	28,577	9,471	30,094	28,044
Adj. R^2	0.986	0.770	0.506	0.090

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.

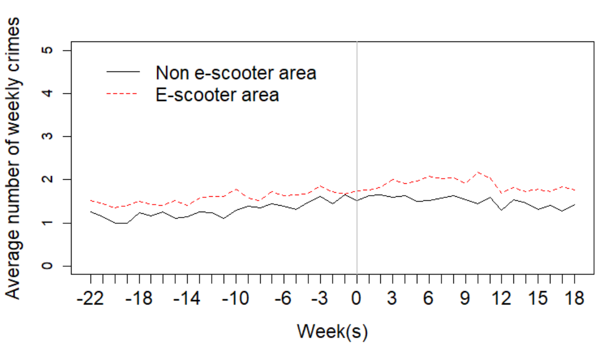
Figure A.1: Parallel Trend Analysis of Four Dependent Variables in the Treatment and Control Areas (Unmatched)



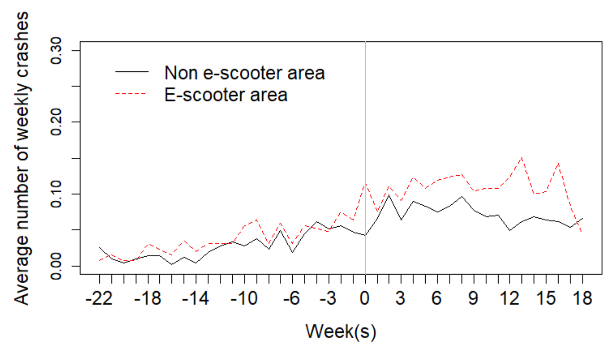
(a) Rideshare



(b) Bikeshare



(c) Crime



(d) Crash

B Main analysis: PSM Matching Details

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

	Means_control		Means_treated		p_value	
Variable	Before	After	Before	After	Before	After
No. of rideshare trips in week -23	4.067	3.905	3.917	3.917	0.339	0.943
No. of rideshare trips in week -22	4.197	4.049	4.073	4.073	0.427	0.890
No. of rideshare trips in week -21	4.320	4.181	4.186	4.186	0.398	0.976
No. of rideshare trips in week -20	4.382	4.253	4.246	4.246	0.380	0.964
No. of rideshare trips in week -19	4.336	4.195	4.190	4.190	0.334	0.973
No. of rideshare trips in week -18	4.348	4.192	4.187	4.187	0.293	0.976
No. of rideshare trips in week -17	4.328	4.183	4.207	4.207	0.428	0.887
No. of rideshare trips in week -16	4.609	4.466	4.440	4.440	0.236	0.865
No. of rideshare trips in week -15	4.619	4.477	4.450	4.450	0.243	0.863
No. of rideshare trips in week -14	4.478	4.295	4.257	4.257	0.136	0.813
No. of rideshare trips in week -13	4.248	4.089	4.126	4.126	0.412	0.814
No. of rideshare trips in week -12	4.205	4.049	4.064	4.064	0.350	0.925
No. of rideshare trips in week -11	4.198	4.039	4.026	4.026	0.251	0.933
No. of rideshare trips in week -10	4.248	4.052	3.996	3.996	0.103	0.737
No. of rideshare trips in week -9	3.991	3.816	3.820	3.820	0.264	0.984
No. of rideshare trips in week -8	4.081	3.895	3.909	3.909	0.275	0.932
No. of rideshare trips in week -7	4.241	4.073	4.040	4.040	0.190	0.842
No. of rideshare trips in week -6	4.085	3.908	3.890	3.890	0.202	0.910
No. of rideshare trips in week -5	4.024	3.843	3.842	3.842	0.244	0.996
No. of rideshare trips in week -4	3.989	3.820	3.836	3.836	0.321	0.922
No. of rideshare trips in week -3	4.000	3.809	3.781	3.781	0.161	0.865
No. of rideshare trips in week -2	3.987	3.772	3.754	3.754	0.125	0.910
No. of rideshare trips in week -1	3.999	3.782	3.773	3.773	0.151	0.960
Income	10.901	10.884	10.951	10.951	0.251	0.165
Population	7.996	7.986	7.987	7.987	0.836	0.969
Young population	7.274	7.308	7.349	7.349	0.094	0.406
POC	7.183	7.177	7.094	7.094	0.155	0.237
Public transport	2.356	2.381	2.413	2.413	0.249	0.562
Parking ticket	1.505	1.500	1.577	1.577	0.258	0.266
Retail visits	1.078	1.411	1.645	1.645	0.000	0.000
Tourism	0.423	0.371	0.419	0.419	0.931	0.253

Notes: POC = People of Color. Young population is the number of inhabitants under 34 years old. Matching variables are used in logged form to handle skewness. Week -23 through -1 refer to each week prior to the entry of e-scooters.

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

	Means_control		Means_treated		p_value	
Variable	Before	After	Before	After	Before	After
No. of bikeshare trips in week -23	2.421	2.397	2.652	2.652	0.219	0.208
No. of bikeshare trips in week -22	2.285	2.266	2.447	2.447	0.402	0.381
No. of bikeshare trips in week -21	1.647	1.652	1.888	1.888	0.166	0.201
No. of bikeshare trips in week -20	1.443	1.455	1.672	1.672	0.164	0.209
No. of bikeshare trips in week -19	2.275	2.254	2.517	2.517	0.206	0.201
No. of bikeshare trips in week -18	2.122	2.120	2.454	2.454	0.077	0.095
No. of bikeshare trips in week -17	2.202	2.177	2.409	2.409	0.269	0.245
No. of bikeshare trips in week -16	2.290	2.261	2.579	2.579	0.121	0.112
No. of bikeshare trips in week -15	2.278	2.243	2.512	2.512	0.221	0.189
No. of bikeshare trips in week -14	2.732	2.690	3.005	3.005	0.161	0.134
No. of bikeshare trips in week -13	2.755	2.705	3.016	3.016	0.185	0.142
No. of bikeshare trips in week -12	2.825	2.783	3.086	3.086	0.179	0.144
No. of bikeshare trips in week -11	3.004	2.943	3.260	3.260	0.201	0.141
No. of bikeshare trips in week -10	3.043	2.984	3.348	3.348	0.115	0.084
No. of bikeshare trips in week -9	3.172	3.099	3.397	3.397	0.270	0.177
No. of bikeshare trips in week -8	3.219	3.181	3.456	3.456	0.235	0.199
No. of bikeshare trips in week -7	3.156	3.096	3.401	3.401	0.208	0.148
No. of bikeshare trips in week -6	3.092	3.061	3.345	3.345	0.206	0.187
No. of bikeshare trips in week -5	3.440	3.378	3.650	3.650	0.289	0.203
No. of bikeshare trips in week -4	3.426	3.376	3.757	3.757	0.096	0.076
No. of bikeshare trips in week -3	3.528	3.452	3.743	3.743	0.293	0.189
No. of bikeshare trips in week -2	3.578	3.530	3.862	3.862	0.163	0.130
No. of bikeshare trips in week -1	3.468	3.427	3.725	3.725	0.213	0.179
Income	10.813	10.865	11.070	11.070	0.001	0.010
Population	8.032	8.003	7.935	7.935	0.158	0.338
Young population	7.310	7.317	7.343	7.343	0.641	0.722
POC	7.217	7.162	6.915	6.915	0.006	0.034
Public transport	2.474	2.495	2.516	2.516	0.596	0.794
Parking tickets	1.633	1.645	1.884	1.884	0.011	0.021
Retail visits	1.653	1.646	1.742	1.742	0.295	0.274
Tourism	0.489	0.455	0.507	0.507	0.784	0.453

Notes: POC = People of Color. Young population is the number of inhabitants under 34 years old. Matching variables are used in logged form to handle skewness. Week -23 through -1 refer to each week prior to the entry of e-scooters.

Table B.3: Summary of Balance Before and After Matching for Crime

	Means_control		Means_treated		p_value	
Variable	Before	After	Before	After	Before	After
No. of crimes in week -23	1.251	1.305	1.519	1.519	0.055	0.168
No. of crimes in week -22	1.140	1.115	1.443	1.443	0.026	0.025
No. of crimes in week -21	1.000	1.103	1.351	1.351	0.004	0.064
No. of crimes in week -20	0.995	1.084	1.408	1.408	0.004	0.037
No. of crimes in week -19	1.230	1.271	1.496	1.496	0.057	0.147
No. of crimes in week -18	1.163	1.183	1.431	1.431	0.037	0.089
No. of crimes in week -17	1.260	1.210	1.405	1.405	0.289	0.188
No. of crimes in week -16	1.100	1.168	1.527	1.527	0.002	0.017
No. of crimes in week -15	1.137	1.172	1.412	1.412	0.039	0.103
No. of crimes in week -14	1.260	1.248	1.569	1.569	0.040	0.052
No. of crimes in week -13	1.230	1.294	1.615	1.615	0.005	0.033
No. of crimes in week -12	1.100	1.252	1.622	1.622	0.000	0.022
No. of crimes in week -11	1.298	1.447	1.786	1.786	0.004	0.070
No. of crimes in week -10	1.386	1.328	1.573	1.573	0.202	0.123
No. of crimes in week -9	1.349	1.317	1.523	1.523	0.240	0.205
No. of crimes in week -8	1.444	1.515	1.733	1.733	0.070	0.218
No. of crimes in week -7	1.384	1.424	1.626	1.626	0.098	0.211
No. of crimes in week -6	1.316	1.309	1.645	1.645	0.028	0.038
No. of crimes in week -5	1.486	1.412	1.695	1.695	0.174	0.090
No. of crimes in week -4	1.605	1.561	1.863	1.863	0.149	0.124
No. of crimes in week -3	1.442	1.473	1.733	1.733	0.049	0.113
No. of crimes in week -2	1.658	1.481	1.664	1.664	0.968	0.246
No. of crimes in week -1	1.516	1.477	1.752	1.752	0.128	0.106
Income	10.897	10.892	10.952	10.952	0.211	0.228
Population	7.991	7.975	7.985	7.985	0.890	0.836
Young population	7.269	7.309	7.347	7.347	0.080	0.435
POC	7.174	7.121	7.089	7.089	0.174	0.659
Public transport	2.380	2.346	2.406	2.406	0.587	0.267
Parking tickets	1.518	1.504	1.583	1.583	0.313	0.227
Retail visits	1.084	1.469	1.641	1.641	0.000	0.007
Tourism	0.420	0.388	0.420	0.420	0.980	0.463

Notes: POC = People of Color. Young population is the number of inhabitants under 34 years old. Demographics are used in logged form to handle skewness. Week -23 through -1 refer to each week prior to the entry of e-scooters.

Table B.4: Summary of Balance Before and After Matching for Crash

	Means_control		Means_treated		p_value	
Variable	Before	After	Before	After	Before	After
No. of crashes in week -23	0.026	0.016	0.008	0.008	0.076	0.412
No. of crashes in week -22	0.009	0.012	0.016	0.016	0.482	0.704
No. of crashes in week -21	0.005	0.008	0.008	0.008	0.708	1.000
No. of crashes in week -20	0.009	0.008	0.008	0.008	0.839	1.000
No. of crashes in week -19	0.014	0.020	0.032	0.032	0.158	0.400
No. of crashes in week -18	0.014	0.020	0.024	0.024	0.456	0.795
No. of crashes in week -17	0.002	0.004	0.016	0.016	0.102	0.178
No. of crashes in week -16	0.012	0.020	0.036	0.036	0.063	0.279
No. of crashes in week -15	0.005	0.008	0.020	0.020	0.109	0.254
No. of crashes in week -14	0.019	0.016	0.032	0.032	0.317	0.243
No. of crashes in week -13	0.028	0.032	0.032	0.032	0.804	1.000
No. of crashes in week -12	0.033	0.028	0.032	0.032	0.933	0.794
No. of crashes in week -11	0.028	0.032	0.056	0.056	0.107	0.212
No. of crashes in week -10	0.038	0.044	0.064	0.064	0.151	0.324
No. of crashes in week -9	0.024	0.032	0.032	0.032	0.538	1.000
No. of crashes in week -8	0.050	0.072	0.060	0.060	0.609	0.622
No. of crashes in week -7	0.019	0.024	0.032	0.032	0.317	0.589
No. of crashes in week -6	0.045	0.056	0.056	0.056	0.559	1.000
No. of crashes in week -5	0.061	0.068	0.052	0.052	0.649	0.507
No. of crashes in week -4	0.052	0.036	0.048	0.048	0.815	0.505
No. of crashes in week -3	0.057	0.056	0.076	0.076	0.419	0.466
No. of crashes in week -2	0.047	0.048	0.064	0.064	0.417	0.483
No. of crashes in week -1	0.043	0.064	0.116	0.116	0.006	0.074
Income	10.891	10.887	10.942	10.942	0.263	0.285
Population	7.982	7.997	7.968	7.968	0.739	0.546
Young population	7.262	7.342	7.334	7.334	0.117	0.874
POC	7.177	7.142	7.072	7.072	0.100	0.344
Public transport	2.380	2.385	2.432	2.432	0.282	0.388
Parking tickets	1.541	1.594	1.651	1.651	0.077	0.386
Retail visits	1.097	1.500	1.643	1.643	0.000	0.028
Tourism	0.407	0.366	0.395	0.395	0.746	0.503

Notes: POC = People of Color. Young population is the number of inhabitants under 34 years old. Demographics are used in logged form to handle skewness. Week -23 through -1 refer to each week prior to the entry of e-scooters.

C Robustness Checks

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

	Shared mobility		Consumer safety	
Variable	Rideshare	Bikeshare	Crime	Crash
E-Scooter × Post entry (DID)	19.253***	-14.426***	0.143***	0.015*
	(3.986)	(3.205)	(0.045)	(0.008)
Week FE	Yes	Yes	Yes	Yes
Census tract FE	Yes	Yes	Yes	Yes
N	16,400	6,642	16,318	16,031
Adj. R^2	0.986	0.752	0.497	0.082

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 for the matched sample.

Table C.2: DID Model Results of the Entry of E-scooters for Alternative Control Group

	Shared mobility		Consumer safety	
Variable	Rideshare	Bikeshare	Crime	Crash
E-Scooter × Post entry (DID)	10.575**	-99.010***	0.057	0.042***
	(4.412)	(18.893)	(0.039)	(0.007)
Week FE	Yes	Yes	Yes	Yes
Census tract FE	Yes	Yes	Yes	Yes
N	14,514	5,453	21,484	20,582
Adj. R^2	0.970	0.782	0.503	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 for the matched sample. The control group is matched from those census tracts that are farther away from the e-scooter boundary (i.e., 2 miles or more). The matching is nearest neighbor with replacement.

Table C.3: Time Discontinuity Analysis: Results for the Entry of E-scooters using Unmatched Sample

	Shared mobility		Consumer safety	
Variable	Rideshare	Bikeshare	Crime	Crash
E-Scooter × Post entry (DID)	22.338***	-11.906***	0.139***	0.017*
	(3.924)	(2.704)	(0.046)	(0.009)
Week FE	Yes	Yes	Yes	Yes
Census tract FE	Yes	Yes	Yes	Yes
N	16,728	5,520	16,608	16,176
Adj. R^2	0.990	0.886	0.508	0.110

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 for the unmatched sample for 12 weeks pre- and post- treatment.

Table C.4: Time Discontinuity Analysis: Results of the Entry of E-scooters using Matched Sample

	Shared mobility		Consumer safety	
Variable	Rideshare	Bikeshare	Crime	Crash
E-Scooter × Post entry (DID)	15.482***	-11.340***	0.156***	0.014
	(4.832)	(2.998)	(0.050)	(0.010)
Week FE	Yes	Yes	Yes	Yes
Census tract FE	Yes	Yes	Yes	Yes
N	12,624	4,992	12,576	12,048
Adj. R^2	0.989	0.887	0.530	0.115

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 for the matched sample for 12 weeks pre- and post- treatment.

Table C.5: Synthetic DID Model Results of the Entry of E-scooters

	Shared mobility		Consumer safety	
Variable	Rideshare	Bikeshare	Crime	Crash
E-Scooter × Post entry (SDID)	13.238**	-1.729	0.135***	0.021**
	(6.551)	(5.875)	(0.046)	(0.009)
N	28,577	9,430	28,372	27,634

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 estimated the model using *sdid* command in STATA and conducting 1,000 placebo replications to derive the variance–covariance matrix associated with the estimates.

Table C.6: DID Model Results of the Entry of E-scooters for High Treatment Intensity

	Shared mobility		Consumer safety	
Variable	Rideshare	Bikeshare	Crime	Crash
E-Scooter × Post entry (DID)	31.229***	-116.109***	0.169***	0.022*
	(9.135)	(13.789)	(0.057)	(0.012)
Week FE	Yes	Yes	Yes	Yes
Census tract FE	Yes	Yes	Yes	Yes
N	10,906	4,264	10,906	10,906
Adj. R^2	0.984	0.802	0.549	0.110

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 for the matched sample. High intensity areas refer to those with higher than median number of e-scooter trips.

Table C.7: DID Model Results of the Entry of E-scooters for Low Treatment Intensity

	Shared mobility		Consumer safety	
Variable	Rideshare	Bikeshare	Crime	Crash
E-Scooter × Post entry (DID)	11.445***	-29.424***	0.041	0.021**
	(1.139)	(4.461)	(0.052)	(0.009)
Week FE	Yes	Yes	Yes	Yes
Census tract FE	Yes	Yes	Yes	Yes
N	10,660	4,264	10,578	9,676
Adj. R^2	0.963	0.672	0.509	0.066

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 for the matched sample. Low intensity areas refer to those with lower than median number of e-scooter trips.

Table C.8: DID Model Results of the Entry of E-scooters Excluding the Weeks of Major Events in Treatment and Control Areas

	Shared mobility		Consumer safety	
Variable	Rideshare	Bikeshare	Crime	Crash
E-Scooter × Post entry (DID)	16.501***	-9.911***	0.121***	0.018**
	(5.184)	(3.577)	(0.043)	(0.008)
Week FE	Yes	Yes	Yes	Yes
Census tract FE	Yes	Yes	Yes	Yes
N	18,936	7,488	18,864	18,072
Adj. R^2	0.985	0.749	0.524	0.097

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 for the matched sample.

Table C.9: DID Model Results of the Entry of E-scooters Excluding the Weeks of Major Events in the Treatment Area

	Shared mobility		Consumer safety	
Variable	Rideshare	Bikeshare	Crime	Crash
E-Scooter × Post entry (DID)	21.072***	-7.403**	0.150***	0.021**
	(4.914)	(3.417)	(0.042)	(0.008)
Week FE	Yes	Yes	Yes	Yes
Census tract FE	Yes	Yes	Yes	Yes
N	18,936	7,488	18,864	18,072
Adj. R^2	0.985	0.745	0.513	0.099

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 for the matched sample.

Table C.10: DID Model Results of the Entry of E-scooters for Post Period Before the First Event in the E-Scooter Area

	Shared mobility		Consumer safety	
Variable	Rideshare	Bikeshare	Crime	Crash
E-Scooter × Post entry (DID)	16.468***	-10.925**	0.152***	0.016*
	(5.828)	(3.757)	(0.044)	(0.009)
Week FE	Yes	Yes	Yes	Yes
Census tract FE	Yes	Yes	Yes	Yes
N	18,410	7,280	18,340	17,570
Adj. R^2	0.983	0.744	0.520	0.097

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 for the matched sample.

Table C.11: DID Model Results of the Entry of E-scooters for Time-Varying Unobservables

	Shared mobility		Consumer safety	
Variable	Rideshare	Bikeshare	Crime	Crash
E-Scooter × Post entry (DID)	17.679***	−6.611**	0.128***	0.018**
	(4.710)	(2.984)	(0.038)	(0.008)
Linear trend	−6.511***	6.538***	0.033***	0.005***
	(0.385)	(0.271)	(0.003)	(0.001)
Quadratic trend	0.092***	−0.113***	−0.001***	−0.000***
	(0.009)	(0.006)	(0.000)	(0.000)
Census tract FE	Yes	Yes	Yes	Yes
N	21,566	8,528	21,484	20,582
Adj. R^2	0.984	0.765	0.519	0.100

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 for the matched sample.

Table C.12: DID Model Results with Nearest-Neighbor Matching within the Caliper = 0.1

	Shared mobility		Consumer safety	
Variable	Rideshare	Bikeshare	Crime	Crash
E-Scooter × Post entry (DID)	28.903***	-35.736***	0.100**	0.015*
	(7.208)	(3.349)	(0.041)	(0.008)
Week FE	Yes	Yes	Yes	Yes
Census tract FE	Yes	Yes	Yes	Yes
N	13,038	3,936	16,810	16,892
Adj. R^2	0.985	0.783	0.458	0.103

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 for the matched sample.

Table C.13: DID Model Results with Nearest-Neighbor Matching within the Caliper = 0.2

	Shared mobility		Consumer safety	
Variable	Rideshare	Bikeshare	Crime	Crash
E-Scooter × Post entry (DID)	32.133***	-27.341***	0.092**	0.017**
	(6.982)	(3.284)	(0.040)	(0.008)
Week FE	Yes	Yes	Yes	Yes
Census tract FE	Yes	Yes	Yes	Yes
N	13,448	4,182	17,794	17,466
Adj. R^2	0.985	0.784	0.499	0.092

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 for the matched sample.

Table C.14: Poisson Model Results of the Entry of E-Scooters

	Shared mobility		Consumer safety	
Variable	Rideshare	Bikeshare	Crime	Crash
E-Scooter × Post entry (DID)	0.064**	-0.069**	0.048*	0.037
	(0.030)	(0.030)	(0.024)	(0.122)
Week FE	Yes	Yes	Yes	Yes
Census tract FE	Yes	Yes	Yes	Yes
N	21,566	8,528	21,279	15,539
Log-likelihood	-96,424.4	-32,732.5	-29,899.0	-3,828.6

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 for the matched sample.

Table C.15: Placebo Test for 2018 Data

	Shared mobility	Consumer safety	
Variable	Bikeshare	Crime	Crash
E-Scooter × Post entry (DID)	-0.017	-0.062	0.003
	(2.976)	(0.040)	(0.010)
Week FE	Yes	Yes	Yes
Census tract FE	Yes	Yes	Yes
N	5,986	21,730	21,730
Adj. R^2	0.808	0.483	0.160

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 for the matched sample. Rideshare data is not available prior to November 2018 so we could not include rideshare in the 2018 placebo test.

Table C.16: Placebo Test for Both Week and Treatment

	Shared mobility		Consumer safety	
Variable	Rideshare	Bikeshare	Crime	Crash
E-Scooter × Post entry (DID)	2.449	-1.741	0.045	-0.005
	(11.283)	(5.821)	(0.108)	(0.010)
Week FE	Yes	Yes	Yes	Yes
Census tract FE	Yes	Yes	Yes	Yes
N	12,098	4,784	12,052	11,546
Adj. R^2	0.988	0.754	0.516	0.073

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 for the matched sample.

Table C.17: Placebo Test for Treatment Only

	Shared mobility		Consumer safety	
Variable	Rideshare	Bikeshare	Crime	Crash
E-Scooter × Post entry (DID)	-0.251	2.394	-0.009	-0.003
	(4.676)	(2.957)	(0.038)	(0.008)
Week FE	Yes	Yes	Yes	Yes
Census tract FE	Yes	Yes	Yes	Yes
N	21,566	8,528	21,484	20,582
Adj. R^2	0.984	0.770	0.519	0.100

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 for the matched sample.

Table C.18: Placebo Test for Week Only

	Shared mobility		Consumer safety	
Variable	Rideshare	Bikeshare	Crime	Crash
E-Scooter × Post entry (DID)	0.500	-0.709	-0.080	0.004
	(11.283)	(5.822)	(0.108)	(0.010)
Week FE	Yes	Yes	Yes	Yes
Census tract FE	Yes	Yes	Yes	Yes
N	12,098	4,784	12,052	11,546
Adj. R^2	0.988	0.754	0.516	0.073

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 for the matched sample.

Table C.19: DID Model Results of the Entry of E-scooters without Outliers

	Shared mobility		Consumer safety	
Variable	Rideshare	Bikeshare	Crime	Crash
E-Scooter × Post entry (DID)	16.483***	-5.831***	0.116***	0.021***
	(1.792)	(2.100)	(0.037)	(0.008)
Week FE	Yes	Yes	Yes	Yes
Census tract FE	Yes	Yes	Yes	Yes
N	21,074	8,364	21,238	20,582
Adj. R^2	0.970	0.798	0.462	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 for the matched sample.

Table C.20: DID Model Results of the Entry of E-Scooter for Alternative Outcomes

	Taxi		Rideshare	
Variable	Short trip	Long trip	Long trip	Total revenue
E-Scooter × Post entry (DID)	33.129***	16.283***	72.459***	103.668***
	(9.798)	(6.216)	(24.288)	(33.390)
Week FE	Yes	Yes	Yes	Yes
Census tract FE	Yes	Yes	Yes	Yes
N	11,972	5,330	15,211	21,566
Adj. R^2	0.970	0.969	0.990	0.984

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 for the matched sample. Long trips refer to the weekly number of trips over two miles at the census tract level and have an average distance of 7.5 miles. Total Revenue refers to the weekly total payments of rideshare trips at the census tract level.

Table C.21: DID Model Results of the Entry of E-Scooter for Retail Visits

Variable	Restaurant	Retail store
E-Scooter × Post entry (DID)	4.036**	5.330**
	(1.244)	(2.022)
Week FE	Yes	Yes
Location FE	Yes	Yes
N	14,842	15,498
Adj. R^2	0.980	0.931

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 for the matched sample.

D Additional Results

Table D.1: Time of Day Analysis for Weekdays

	Rideshare		Bikeshare		Crime		Crash	
Variable	Peak	Non-peak	Peak	Non-peak	Peak	Non-peak	Peak	Non-peak
E-Scooter × Post entry (DID)	4.196***	8.734***	-2.586	-9.488***	0.003	0.033	0.003	0.006
	(1.244)	(3.053)	(1.654)	(2.439)	(0.011)	(0.025)	(0.003)	(0.004)
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census tract FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	20,910	15,662	2,132	3,608	21,730	21,730	21,730	21,730
Adj. R^2	0.965	0.985	0.831	0.751	0.105	0.341	0.041	0.041

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 for the matched sample.

Table D.2: Time of Day Analysis for Weekend

	Rideshare		Bikeshare		Crime		Crash	
Variable	Peak	Non-peak	Peak	Non-peak	Peak	Non-peak	Peak	Non-peak
E-Scooter × Post entry (DID)	2.200***	0.643	-7.308***	-12.229***	0.016*	0.073***	0.001	0.006*
	(0.625)	(1.481)	(1.481)	(2.647)	(0.010)	(0.023)	(0.002)	(0.004)
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census tract FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	20,910	15,867	1,640	3,526	21,730	21,730	21,730	21,730
Adj. R^2	0.963	0.960	0.668	0.706	0.086	0.318	0.007	0.020

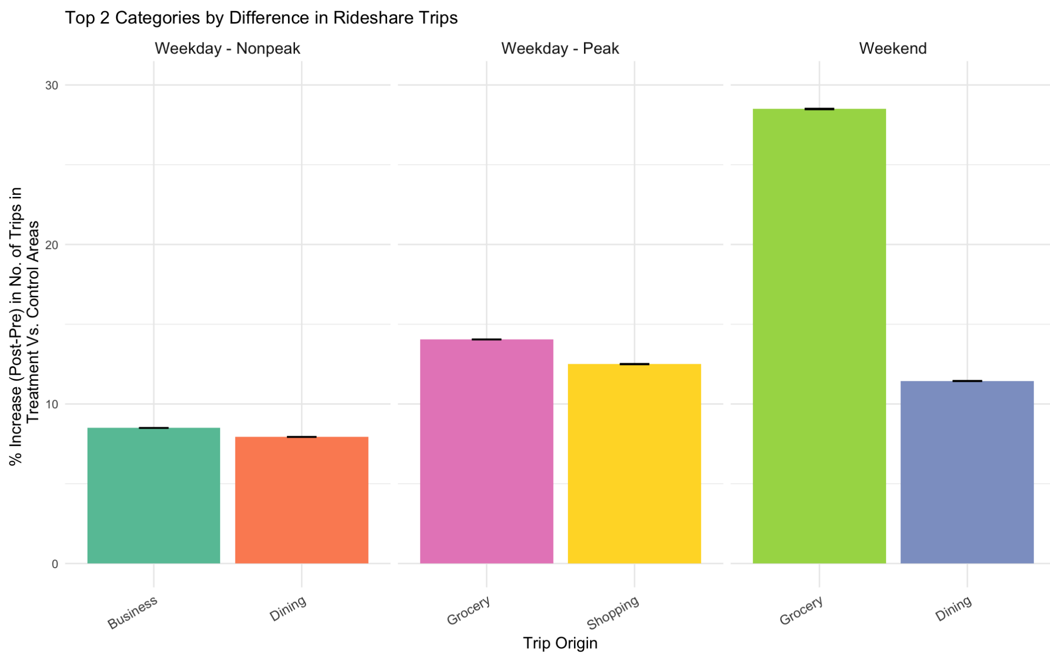
Notes: Robust standard errors clustered by census tract are in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.10. DID = Difference-in-Differences. FE = Fixed effects. N = No. of observations for the matched sample.

Table D.3: DID Model Results of the Entry of E-Scooters for Heterogeneity by Income and Age

	Shared mobility		Consumer safety	
Variable	Rideshare	Bikeshare	Crime	Crash
DID	-456.985*	153.671**	0.264	0.090
	(179.797)	(62.058)	(0.882)	(0.185)
DID × Log(Older)	16.375*	1.077	-0.120*	0.002
	(9.791)	(6.379)	(0.065)	(0.013)
DID × Log(Income)	33.176***	-16.568***	0.067	-0.008**
	(11.617)	(4.766)	(0.073)	(0.015)
Week FE	Yes	Yes	Yes	Yes
Census tract FE	Yes	Yes	Yes	Yes
N	21,566	8,528	21,484	20,582
Adj. R^2	0.984	0.789	0.520	0.103

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 for the matched sample. We also include the main effects and two-way interaction terms of the moderating variables with each term (i.e., *E-scooter* and *Post entry*) but do not report them to save space.

Figure D.1: Change in Percentage of Rideshare Trips by Trip Purpose and Timing



E Dynamic Effects of E-Scooters Over Time

Table E.1: DID Model Results of the Entry of E-scooters by Different Time Periods

	Shared mobility		Consumer safety	
Variable	Rideshare	Bikeshare	Crime	Crash
Week 4	15.80	-12.21*	0.01	0.01
	(10.46)	(7.29)	(0.07)	(0.01)
Week 8	11.60*	-12.67**	0.11**	0.01
	(6.74)	(5.00)	(0.05)	(0.01)
Week 12	16.47***	-10.92***	0.15***	0.02*
	(5.83)	(3.76)	(0.04)	(0.01)
Week 16	17.07***	-8.04**	0.12***	0.02***
	(4.94)	(3.15)	(0.04)	(0.01)

Notes: Robust standard errors clustered by census tract are in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. DID = Difference-in-Differences. Week and census tract fixed effects are included. Week refers to the number of post-treatment weeks.

Figure E.1: Dynamic Effects of the Entry of E-scooters on Ridesharing

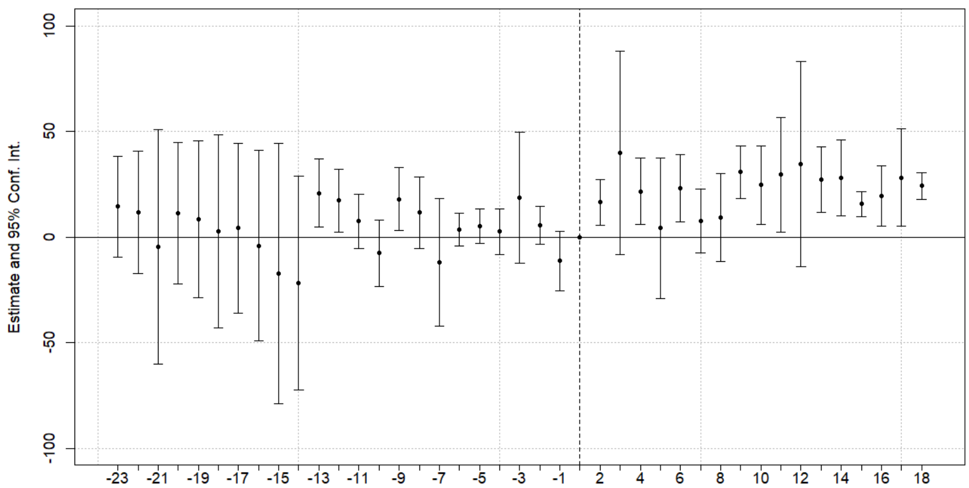


Figure E.2: Dynamic Effects of the Entry of E-scooters on Bikesharing

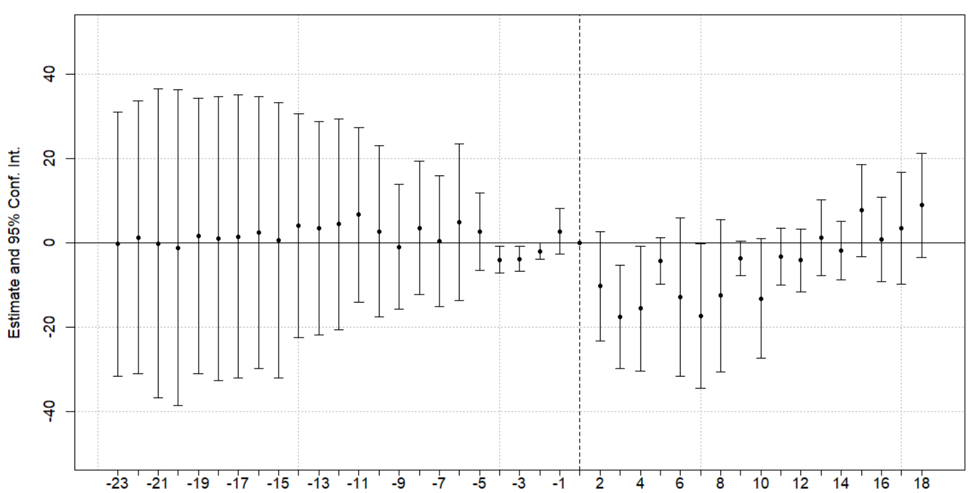


Figure E.3: Dynamic Effects of the Entry of E-scooters on Crime

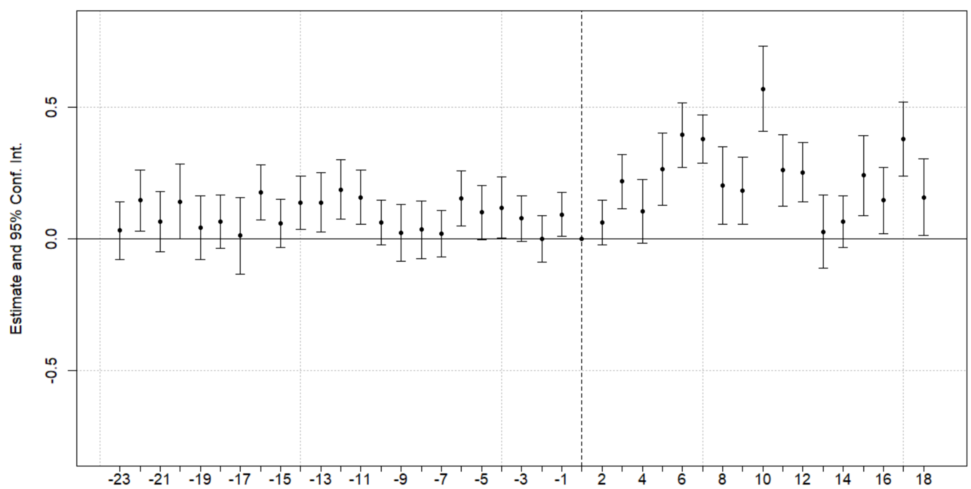
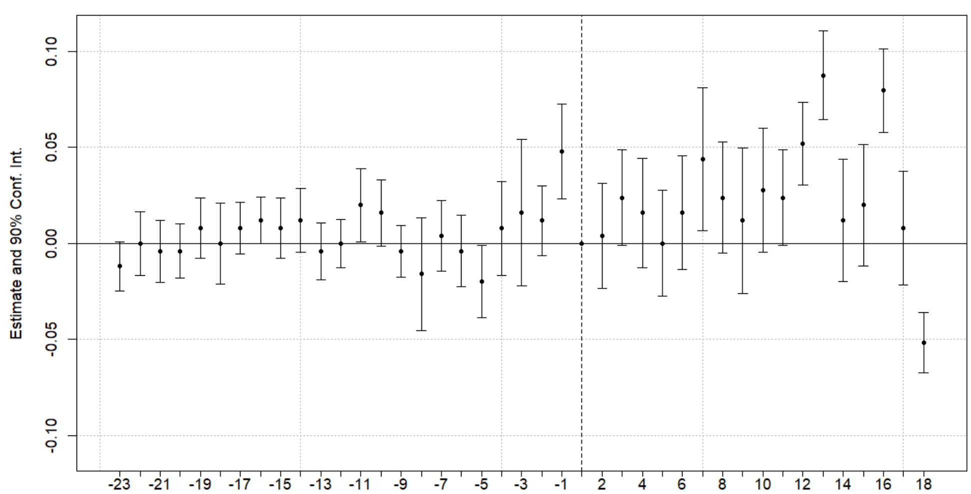


Figure E.4: Dynamic Effects of the Entry of E-scooters on Crash



F Categories of Places-of-Interest (POI) for Mechanism Analysis

Table F. 1: The Categories of Point of Interest (POI)

ID	Categories	Examples
1	Business	Banks, auto shops, government offices, and postal service
2	Grocery	Grocery stores, specialty food stores, and convenience stores
3	Recreation	Museums, amusement parks, and arcades
4	Dining/Restaurant	Restaurants and other eating places, and drinking places
5	Other shopping	Clothing stores, department stores, and bookstores

Notes: Refer to Liu et al. (2017) and Espinoza et al. (2019)

G App Screenshots

Figure G.1: Screenshots from the Research App Companion: Main Features