Can Apps Save the Planet? Enhancing Urban Mobility and the Environment through Tech Adoption

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Abstract

This paper investigates the impact of integrating bike-sharing into Lyft's ride-hailing app in New York City, which eliminated informational and booking frictions when switching between ride-hailing and cycling. Using a rich dataset from bike-share systems in New York City and Philadelphia, we employ a triple-difference estimator to compare ridership trends across both cities, before and after the integration, for subscribers (monthly or annual pass holders) and non-subscribers (day-pass or single-ride users). Our results show a 13% overall increase in bike-share ridership in New York City, driven entirely by non-subscribers—who represent the marginal users of the system—as their usage surged by 122%. This increase is concentrated during rush hours, supporting the hypothesis that bike-share becomes more attractive when roads are congested, and the marginal private and social costs of ride-hailing trips are higher. Finally, we collected car ride-hailing data and find suggestive evidence that around 7% of Lyft ride-hailing trips were substituted by non-subscriber riders. These findings provide valuable insights for policymakers on expanding mobility choices, promoting cycling, and reducing transportation costs. By facilitating a shift toward bike-share, such integrations have the potential to significantly alleviate congestion, improve air quality, and lower carbon emissions.

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1 Introduction

Approximately half of the world population resides in dense urban areas, a proportion projected to increase to over two-thirds by midcentury (United Nations and Social Affairs, 2018). This rapid urbanization exacerbates existing urban externalities such as traffic congestion and air pollution, imposing substantial costs on residents through degraded air quality, increased travel times, and strained public infrastructure. These patterns highlight the need for policies that effectively mitigate such externalities, particularly for short-distance travel as vehicle trips in many large cities tend to be relatively short.[1]. Various policies have been debated and implemented over the last few decades to deal with these challenges, including congestion charges (Leape, 2006; Yang et al., 2020), stricter vehicle emission standards (Knittel and Davis, 2019; Jacobsen et al., 2023) and low emission zones (Wolff, 2014). Concurrently, promoting cycling has emerged as another promising approach, with cities such as Paris, London, and New York aggressively investing in bicycle infrastructure. Bicycles, which require less road space compared to motor vehicles, offer an environmentally friendly alternative capable of reducing congestion, mitigating local air pollution, and also lowering the carbon footprint of urban transport (Giménez-Nadal et al., 2022; Gössling and Choi, 2015; Hamilton and Wichman, 2015; Chapman, 2007).[2]

Bike-sharing systems have become a widespread and pivotal urban mobility strategy with a projected global market of over USD 13.7 billion by 2026 (Rotaris et al., 2022). These systems provide short-term bicycle access where users pick up, ride, and drop off bikes through a network of self-service docking stations (Shaheen, Guzman, et al., 2010). The literature discussing the factors leading to the adoption of shared bicycles is primarily qualitative in nature and the few non-causal empirical studies mainly explore what characteristics of a bike-share system are important to users, issues of land-use, and how the introduction of electric bicycles influence ridership (Faghih-Imani et al., 2017; Médard de Chardon et al., 2017; He et al., 2019). The literature also comments on ease-of-use characteristics, such as user experience (Fishman et al., 2012) and convenience (Hazen et al., 2015), but to the best of our knowledge, there are no empirical studies that quantify the causal effect of how new digital app technologies can influence ridership and reduce urban congestion forces.

This paper addresses this critical gap in knowledge by examining how technological improvements that simplify bike-sharing services—through the integration of transportation service information into a major mobile app—affect ridership and the environment. In particular, in 2018, the ride-hailing company Lyft acquired the public bike-share operator Motivate, and in May 2019, it integrated bike-sharing services into its proprietary mobile app (Bradshaw, 2018) in New York City (NYC). This change streamlined the

[1]For example, the shares of vehicle trips in New York City which are less than 1 and 5 miles are 25% and 70% respectively (New York City Department of Transportation, 2022)

[2]Transportation is a major contributor to CO_2 emissions, often accounting for 20% to 40% of total emissions in major cities (Isik et al., 2021).

bicycle rental process by consolidating bike-sharing with Lyft's widely used ride-hailing platform (Figures A1 and A2 show the platform's user interface before and after the service integration).

We estimate the impact of this integration on three key outcomes: (1) changes in bike-share ridership; (2) the substitution effect between ride-hailing and biking and (3) transport emissions. To overcome confounding factors, we exploit quasi-experimental variation from three distinct sources. Our primary empirical approach employs a triple-difference estimator, comparing shared bike ridership in NYC and Philadelphia before and after the integration of bike-sharing into the Lyft app in May 2019. Additionally, we differentiate between subscribers and non-subscribers to bike-share services. Subscribers, defined as riders with at least a monthly subscription in NYC and Philadelphia, use the system regularly and are familiar with both the technology and docking station locations. In contrast, non-subscribers rent cycles as day-pass or single-ride users. This group is less familiar with station locations. For non-subscribers, integrating bike-sharing into the Lyft app likely provided greater informational value. When searching for a Lyft ride-hail, they could now recognize that renting a bike might be cheaper and faster, depending on road congestion. Additionally, because their payment details were already stored in the Lyft app, they could use the Citi Bikes without needing to download a separate app. We refer to these day-pass or single-ride users as the "marginal users" of the bike-share system.

By incorporating these distinctions, our approach not only compares NYC before and after May 2019 but also leverages Philadelphia as a control city and the variation in user type. We selected Philadelphia as the control city because it is the closest major city to NYC with a large-scale bike-sharing service, yet its Lyft ride-hailing app did not integrate public bikes. Its proximity to NYC means that both cities share similar regional macroeconomic trends, including employment patterns and broader economic conditions. Additionally, Philadelphia and NYC experience comparable seasonal and weather patterns, which are crucial factors influencing bike ridership.

The empirical analysis which relies on a rich, publicly available dataset of bicycle trips from the Indego (Philadelphia) and Citi Bike (New York City) systems yields four key findings. First, using a difference-in-differences estimator, we find that integrating Citi Bike into the Lyft app in May 2019 led to a statistically and economically significant increase in ridership in NYC, with an overall rise of 13%. Second, we decompose this effect to distinguish between subscribers and non-subscribers (marginal users). The increase is driven entirely by the marginal users, whose ridership more than doubled (surged by 122%) as estimated using a triple-difference approach, which main results are displayed in Figure 1. This Figure shows that NYC, relative to Philadelphia, experienced a sharp increase in day-usage bikers that coincides with the date after the Lyft app integration in May 2019. Third, this sharp increase is concentrated during rush hours when biking increased by 216%, supporting the hypothesis that bike-share becomes more

attractive when roads are congested and the private costs of ride-hailing (e.g., due to Lyft's dynamic surge pricing and high value of time costs in NYC) and social costs of ride-hailing (e.g., congestion externalities amplify time costs as well as air pollution costs in stop and go traffic)—are higher. Finally, we collected ride-hailing data and find suggestive evidence that around 7% of Lyft ride-hailing trips are substituted by non-subscribers.

Our results contribute significantly to both academic literature and ongoing policy debates. We add to the growing research and discussion on the costs and benefits of integrating multiple mobility services into a single app.[3] Aggregator platforms are widespread in industries such as hospitality (e.g., Booking.com), food delivery (e.g., Deliveroo in the UK), real estate (e.g., Zillow in the US), and air travel (e.g., Expedia). However, unlike other sectors where aggregators consolidate services from multiple providers, mobility operators have largely resisted such integration. Many firms, including Uber, have created "walled gardens" by restricting access to their data and positioning themselves as the exclusive aggregator of their own services—effectively excluding competitors like Lyft. Due to strong indirect network effects in two-sided markets (Rochet and Tirole, 2006), platform businesses initially compete for market share but ultimately pursue winner-take-all strategies.[4]

To counter these monopolistic tendencies, several governments have introduced regulations requiring mobility operators to share real-time data on availability and pricing with third-party aggregators. Examples include Finland's 2018 Taxi Law, British Columbia's regulatory framework in Canada (Wolff, 2019), and the European Union's initiative to create a pan-European real-time travel data system. The EU effort, in particular, aims to enable seamless multimodal trip planning and booking across cities and countries via a single app, reducing the need for users to navigate multiple platforms.[5]

Despite these policy efforts, the ride-hailing industry has consistently resisted open-data mandates, arguing that they undermine business models by enabling third-party platforms to facilitate bookings. Since open-data regulations are still in their early stages, empirical evaluations of their impact remain scarce. Our study provides the first natural experiment of MaaS integration by analyzing Lyft's incorporation of both bike-sharing and ride-hailing into a single app. While our findings focus on NYC and Philadelphia, they offer broader insights into MaaS adoption in cities with dense transportation networks and the regulatory debates surrounding open-data mandates. Specifically, our results provide policymakers with empirical evidence on how reducing information and booking frictions through MaaS integration influences user behavior—insights that will be increasingly

[3]In transportation, this concept is known as "Mobility as a Service" (MaaS), referring to the seamless integration of various transportation options into a single platform.

[4]Uber, for instance, now offers boat trips in London, helicopter services in New York City, ride-hailing, and electric bikes, with plans to expand into autonomous vehicles.

[5]As discussed in Wolff (2019), open-data policies have significant implications for competition in mobility markets. Digital platforms often exhibit strong network effects, leading to natural monopolies. Open-data regulations could counteract this tendency by allowing smaller operators to display their services on aggregators, fostering competition.

relevant as governments expand open-data legislation and autonomous services evolve.

Our study also contributes to the academic literature on urban transportation and congestion externalities. Prior research has examined the role of public transportation investments and congestion pricing in mitigating these externalities (Leape, 2006; Yang et al., 2020). However, relatively little is known about how digital platform integrations that reduce informational and booking frictions affect urban transportation choices, which in turn can influence both local and global externalities. By examining how Lyft's integration of bike-sharing affected mode substitution, we provide the first evidence on how such integration may mitigate congestion and its associated negative effects. Additionally, ride-hailing services have been found to exacerbate congestion in major cities (Tarduno, 2021; Diao et al., 2021). In particular, the arrival of ride-hailing into NYC (UBER in 2011 and Lyft was introduced to NYC in 2014) has been found to substantially increase congestion (Schaller, 2021). Since then, the number of for-hire vehicles has tripled, from fewer than 40,000 in 2010 to over 120,000 in 2019, leading to a sharp increase in vehicle miles traveled as drivers spend an estimated 42% of their time deadheading without passengers in NYC (New York City Taxi and Limousine Commission, 2019, 2023). Our findings suggest that MaaS integration could help alleviate this trend by encouraging substitution from ridehailing to biking.

Our work also contributes to the literature on digital platforms, search frictions, and the sharing economy. Digital platforms increasingly integrate services to reduce transaction costs and enhance consumer choice (Goldfarb and Tucker, 2019). In transportation, studies have documented how ride-hailing platforms such as Uber and Lyft affect consumer surplus and labor market dynamics (Cohen et al., 2016; Angrist et al., 2021). We extend this strand of research by examining how bike-sharing integration within a ride-hailing app influences user behavior and facilitates a transition toward more sustainable transportation options.

This paper also relates to the literature on consumer behavior and mode choice in transportation. The heterogeneous response between subscribers and non-subscribers suggests that digital integrations primarily benefit marginal users, who face higher informational and transactional frictions. This aligns with research on behavioral inertia in transportation decisions (Anderson, 2014) and studies on how subsidies and price incentives influence public transit ridership (Parry and Small, 2009). The observed increase in bike-share usage during peak hours further supports the idea that consumers substitute toward cycling when the private and social costs of ride-hailing are highest.

Finally, our findings contribute to the growing literature on the role of public bicycle-sharing in urban transportation and the factors influencing its adoption relative to other mobility options. In particular, our study is closely related to Hamilton and Wichman (2018), who show that the availability of bike-sharing infrastructure reduces traffic congestion by more than 4% within a neighborhood. As bike-sharing systems continue to expand across cities and continents (Shaheen, Zhang, et al., 2011), there is a

pressing need for further research on this topic.

The rest of this paper is organized as follows. Section 2 reviews the history of bike-sharing and explains the two bike-share systems relevant to this study, Citi Bike of NYC and Indego of Philadelphia. Section 3 describes the data used in this paper. Section 4 explains the triple-difference methodology used for estimating our causal effect. Section 5 shows the results of our model. Section 6 performs a series of robustness tests to ensure our triple-difference results can be interpreted as causal. Section 9 discusses the results and the implications of them, along with the potential limitations of our study. Finally, Section 10 concludes.

2 Background on Bike-sharing Systems

Bike-sharing has significantly increased in popularity over time, evidenced by just 5 systems operating globally in 2000 and growing to over 2000 systems across 92 countries in 2022 (*The Meddin Bike-sharing World Map Report* 2022). Bike-sharing carries the general purpose of increasing mobility around a city, however there is evidence that it can serve either as a substitute for other modes of transportation, or as a complement. For example, in Washington DC, Montreal, and Toronto, 48%, 50%, and 44% of surveyed users, respectively, reported bike-share programs resulted in a decrease in transit by rail. Although, in the same cities, 7%, 11%, and 9% of surveyed users, respectively, reported a response of increasing rail use (Martin and Shaheen, 2014). Importantly, respondents in all cities reported a reduction in driving due to bike-share access by as much as 51% (Martin and Shaheen, 2014). These statistics highlight that bike-sharing systems are helpful to users in different ways, depending on whether their traditional habits of mobility can be replaced entirely by a bicycle, or instead optimized in the first-and-last mile of their journey that includes other forms of transit (Martin and Shaheen, 2014).

In North America, Bike-sharing systems have evolved since their original debut in Portland, Oregon in 1994, where bicycles were left unlocked and free to use throughout the city (Shaheen, Guzman, et al., 2010). Now, bike systems are primarily "third generation", where programs incorporate information technology into their renting and payment procedure, or "fourth generation", where additional efforts are made such as improved bike-share redistribution, better integration with public transportation, and the electrification of bicycles available for use (Shaheen, Guzman, et al., 2010). Two programs that characterize aspects of the third and fourth generation systems are Citi Bike in NYC, and Indego in Philadelphia.

2.1 Citi Bike

Citi Bike began operating in NYC in 2013 and was managed by Motivate in partnership with the NYC Department of Transportation in 2014 (Citi Bike, 2020a). In July 2018, Motivate was purchased by the ride-hailing company Lyft (Sandler, 2018), who eventually

integrated the service with their mobile application, launching the newly consolidated app for users in NYC in May 2019 (Citi Bike, 2020b). In 2019, Citi Bike boasted the largest fleet in the nation of 12,000 bikes (Dickey, 2019), with over 143,000 members (Citi Bike, 2020a). The bike rental procedure for Citi Bike is detailed in Appendix A.1.

Pre-acquisition Before Lyft acquired Motivate, users could choose between short-term single rides, 1-day or 3-day passes, and long-term annual subscriptions. The single ride cost $3 with rides longer than 30 minutes charged an extra $3 per additional 30 minutes (Citi Bike, 2018, 2019a). The 1-day and 3-day passes cost $12 and $24, respectively, and included unlimited 30-minute rides, with rides longer than 30 minutes charged an extra $4 per additional 15 minutes. The annual subscription cost $169 and included unlimited 45-minute rides, with rides longer than 45 minutes charged an extra $2.50 per additional 15 minutes (Citi Bike, 2019d).

Post-acquisition After Lyft's acquisition of Motivate, the ride options and pricing structures remained the same (Citi Bike, 2019e). The Citi Bike rental procedure post-acquisition by Lyft is largely the same but includes some key additions. Like before, users can rent a bike through a physical kiosk, or by using the Citi Bike mobile app. However, users also have the option of renting a bike through the Lyft mobile app, where traditionally a car-based ride is sourced from, displayed in Figure A2. Once the Lyft app has been downloaded, and payment information provided, a user can unlock and begin riding a bike by scanning a QR code, rather than acquiring and inputting a 4-digit code. This is an important detail because it demonstrates the contrast between a high friction list of steps required for renting a bicycle pre-acquisition, to the low friction procedure for renting a bicycle post-acquisition. The Lyft app also allowed users to link their Citi Bike annual subscription (Citi Bike, 2019b). Using the Lyft app for unlocking a Citi Bike was immediately advantageous because it consolidated a service that many people already used. For example, nationwide, in the first quarter of 2019, Lyft had reported 20.4 million active users and captured roughly 30% of the ride-hailing market share (Iqbal, 2023). While usage data is not available for NYC specifically, it can be inferred that Lyft carried a strong market presence and sense of familiarity to those who travelled around the city, thus playing a role in the success of their integrated bike-share launch in 2019.

2.2 Indego

The Indego public bicycle program, operated by Bicycle Transit Systems in partnership with the City of Philadelphia, started operating in 2015 (Indego, 2020a). In 2019, the program reported 138 stations holding roughly 1,500 bikes (Indego, 2020b). Indego offered daily, monthly, annual, and "flexible" passes. Daily passes cost $10/day, with unlimited 30-minute rides and an extra $4 for every additional 30 minutes. Monthly subscriptions

cost $17/month, with unlimited 60-minute rides, and an extra $4 for every additional 60 minutes. Annual subscriptions cost $156 for a year, with unlimited 60-minute rides, and an extra $4 for every additional 60 minutes. (Indego, 2018b). Indego Flex passes served as a hybrid option where users could pay $10 annually and $4 per hour for all trips (Indego, 2018a). During the window of study from 2018 to 2019, Indego did not change ownership, but made some changes to their pricing structure. On May 15, 2019 (Indego Bike Share, 2019), Indego increased the day-pass rate to $12, and introduced a 15 cent/per minute charge for all subscription types for rides with a duration longer than the additional time allotment (Indego, 2019a,b) [6] . The bike rental procedure for Indego is detailed in Appendix A.2 and Figure A3 displays the application interface.

3 Data

3.1 Bicycle system data

Public bicycle ridership data in New York City is collected through Citi Bike system data, now provided by Lyft (Citi Bike, 2023). The data is structured at the trip level beginning in June 2013 through the most recently completed month. A subset of data collected for 2018 and 2019 is used for this study. Each observation consists of data such as the start and end time for each ride, the geographical coordinates for the start and end station of each ride, and a user type (indicating the type of rental subscription used on a trip) for the user who rented the bike.

Ridership data in Philadelphia is collected through Indego system data, provided by the City of Philadelphia (Indego, 2023b). Indego data is also structured at the trip level, starting in April 2015 through the most recently completed quarter. A subset of 2018 and 2019 data is also used for this analysis. The observations contain similar data fields to that of Citi Bike, with the addition of a bike type (standard or electric). Citi Bike later adds bike type details, but not until 2020 and therefore electric bicycles are not a focus of this study.

3.2 Weather controls

Weather data is collected from local weather stations for each city, provided by NOAA and the National Center for Environmental Information (Vose et al., 2014). The Philadelphia International Airport has collected weather data daily since 1940, with a 99% coverage rate and JFK International Airport in NYC has collected weather data daily since 1948, with a 100% coverage rate. From each dataset we use average temperature, precipitations, snow fall and depth, and average wind speed.

[6] We explore how these pricing changes may affect our treatment effect in Section 6

4 Methodology

4.1 Event study and parallel trends

Identification through difference-in-differences requires having met the PTA to estimate a causal relationship. Satisfying the PTA cannot be proven, given that a world does not exist where we can observe the treatment group had they not been treated (Cunningham, 2021). However, we can perform several visual and statistical tests to argue that our two study areas do not evolve in ridership differently over time, and that our treatment is exogenous (Cunningham, 2021). In other words, we must show that Philadelphia provides a suitable counterfactual to NYC for public bike ridership.

Figure 2 lets us inspect the trend among non-subscribers between NYC and Philadelphia. Visually, both lines seem to follow parallel trends prior to treatment, with NYC's non-subscriber trips increasing relative to Philadelphia's non-subscriber trips after the treatment. In addition to the visual inspection of raw data trends, we can statistically test if the difference between NYC and Philadelphia ridership trends is significant in the periods prior to and following the treatment. To do so, we specify an event-study model, given in Equation 1. We separately regress both non-subscriber ($g = 1$) and subscriber ($g = 0$) daily (d) ridership for cities j, $ln(Trips_{djg})$, on the interaction between relative pre- and post-periods k around treatment (period -1 serving as the reference period), with city j and month m fixed effects:

$$ln(Trips_{djg}) = \alpha + \sum_{k=m_0}^{-1} \beta_k \times Treat_j + \sum_{k=1}^{m_1} \beta_k \times Treat_j + \phi_j + \gamma_m + \varepsilon_{djg}. \quad (1)$$

4.2 Difference-in-differences

Next, we estimate the aggregate impact of the integration of bike-sharing in Lyft's ride hailing app on overall ridership. To do so, we run a difference in differences (DD) specification comparing NYC (where the integration occurred) with Philadelphia (where it did not), before and after the integration. The model is given by the following equation:

$$ln(Trips_{jd}) = \beta_0 + \beta_1 Treat_j + \beta_2 Post_d + \beta_3 Treat_j \times Post_d + \beta_4' X_{jd} + \gamma_m + \varepsilon_{jd} \quad (2)$$

where $ln(Trips_{jd})$ represents the logarithm of trips taken on a public bike in city j, on day d. $Treat_j$ is equal to 1 for trips made in NYC, and 0 for those made in Philadelphia. $Post_d$ takes the value of 1 if the day is greater or equal to May 22, 2019, and 0 otherwise. X_{jd} represents a vector of covariates (weather) used in some specifications, and γ_m are month of the year fixed-effects. The coefficient of interest in this specification is β_3, which captures the average treatment effect of the integration on NYC's total ridership. By controlling the effect of the intervention in NYC with Philadelphia, we are able to isolate

the impact of integrating bike-share in the ride haling app net of city fixed effects and trends in ridership common to both cities. Philadelphia is a well suited control group to NYC because it is a large city in close proximity to NYC, it has a bike share program, and experiences similar weather patterns and socio-economic shocks that may affect ridership.

4.3 Triple-differences

In order to unpack the change in overall ridership, we use a triple-differences (DDD) estimator to isolate the causal effect of transit app aggregation on different types of users. To achieve this, we leverage three sources of variation in the public bike-share data. First, as in the DD estimation, we compare ridership before and after May 22, when Lyft's new Citi Bike offering launched in their ride hailing mobile app. Second, we compare NYC, where Lyft's acquisition and therefore treatment occurred, to Philadelphia, where Lyft does not operate therefore serving as our control. Lastly, we split bike-share riders into two groups: subscribers (annual or monthly pass holders) and non-subscribers (single-ride or day-pass holders). We argue that non-subscribers are the group of bike-share riders most likely to be impacted by the intervention. Indeed, non-subscribers are casual riders defined as not holding an annual or monthly subscription, who are therefore less likely to have the bike-share app installed on their phone and less likely to have the habit of using that mode of transport. The integration of bike-share information and booking capability on the ride-hailing app should thus incentivize mostly this group of non-subscribers to respond to the treatment and start using bike-share. The subscriber group, on the other hand, acts a reliable placebo, as they are less likely to change their cycling habits after the app integration. The triple-differences model lets us test that hypothesis by interacting the treatment and post indicators with an indicator on the type of riders. The following DDD model is estimated:

$$\begin{aligned} ln(Trips_{jdg}) = \beta_0 &+ \beta_1 Treat_j + \beta_2 Post_d + \beta_3 NonSubscriber_g \\ &+ \beta_4 Treat_j \times NonSubscriber_g + \beta_5 NonSubscriber_g \times Post_d \\ &+ \beta_6 Treat_j \times Post_d + \beta_7 Treat_j \times NonSubscriber_g \times Post_d \\ &+ \beta_8' X_{jd} + \gamma_m + \varepsilon_{jdg}. \end{aligned} \tag{3}$$

The terms in 3 are similar to those in Equation 1. We add $NonSubscriber_i$ as an indicator variable equal to 1 if the trips are made by non-subscribers, and 0 otherwise. We also add a third subscript g that represents the type of riders. Our coefficient of interest is β_7, which captures the differential effect of the treatment on non-subscribers relative to subscribers, net of city fixed effects, common time trends (first two differences), and some city-specific time-variant effects (third difference).[7]

[7]Our third difference may not entirely remove all potential city-specific time-invariant bias because it

5 Results

5.1 Event study and parallel trends

Figure 2 can be used to visually check for parallel trends. Counts of ridership for each city are plotted and appear to have similarly evolving trends throughout the pre-period until our treatment occurs on May 22, 2019 (week 21), where they begin to diverge throughout the post-period. Visually confirming that our treatment and control cities have similar trends of ridership of non-subscribers before the treatment is one helpful piece of evidence in arguing for the validity of Philadelphia as a suitable counterfactual.

Figure 4 plots the β_k from Equation 1 for periods before and after the intervention. In the period prior to the integration of bike-share information on the ride hailing app in NYC (left of the dotted vertical line), we see no statistical differences in the ridership of non-subscribers trends between NYC and Philadelphia. The lack of differences between treatment and control lends support to the parallel trends assumption our strategy relies on, and the validity of Philadelphia as a control city for NYC. After the treatment, NYC non-subscriber ridership increases compared to its Philadelphia counterpart, suggesting that the integration increased ridership of that group. Conversely, subscriber ridership displays non statistically significant differences before as well as after treatment between NYC and Philadelphia, which indicates that the treatment effect mostly runs through non-subscribers.

5.2 Difference-in-differences and triple-differences

Table 1 reports the results for both the DD (columns 1 and 2) and DDD (columns 3 and 4) estimations. In column 1 and 2, we show that by integrating bike-share information to the ride hail app and making booking easier, Lyft increased bike-share ridership by 13% compared to Philadelphia, the control city. We unpack this result by rider groups in order to understand the source of this increase in column 3 and 4. The coefficient associated with the triple interaction suggests that launching an easy to use and simplified bike-share rental system in the Lyft app results in a 122% increase in ridership of non-subscribers in NYC, relative to the counterfactual where Citi Bike never received the treatment.[8] A 122% increase in non-subscriber ridership equates to an average of 42,000 more trips weekly in NYC through the the public bike-share.

Putting this change in ridership in perspective, the New York MTA estimates on average roughly 0.5 kilograms of carbon is offset for each Citi Bike trip (Citi Bike, 2019c). This means our estimated treatment effect results in an average of 21 metric tons of carbon offset compared to a scenario where the treatment never occurred.

is possible that factors such as improved bicycle infrastructure influences subscribers and non-subscribers differently. Section 9.2 discusses this in further detail.

[8]For all the percentages calculated, we apply the log transformation (exp(b)-1)*100 when the estimated DDD parameter is above|0.1|.

6 Robustness checks

In addition to the event study depicted in Figure 4, we can visually check how the trend in subscriber ridership evolves across cities before and after the time of treatment. Figure 3 shows that ridership for the subscriber group stayed fairly constant. In particular, there is no sharp discontinuity in the NYC subscriber ridership around the time of the treatment.

Column 1 and 2 of Table 1 reported the overall of treatment on overall ridership in NYC, while columns 3 and 4 show the result of a triple-differences estimation disentangling the treatment effect by user group. In Table 2 we report estimates of treatment when running the difference-in-differences model separately for both groups.[9] The results confirm those reported in Table 1: the effect of treatment on subscribers is very small around 4.5%, while the impact on non-subscribers reaches 130%.

Lastly, we test the effect of Indego's pricing change on May 15, 2019 which increased the price of a day-pass from $10 to $12 and introduced a marginal 15 cent per minute charge for each additional minute beyond the additional 30 minute allotment. To perform this test, we employ a DDD estimation using Equation 3 and instead implement a "post-period placebo" representing the period after the pricing change (May 15) but before the primary treatment where Lyft integrated Citi Bike's services within their app (May 22). The results are displayed in Table 6. We find that Citi Bike ridership increased by 21% in the placebo post-period for non-subscribers, relative to Indego subscriber ridership before the pricing change. Therefore, using the results of this test, we can disentangle the effect of Indego's increase in the day-pass rate, 21%, from the primary treatment effect, 122%, resulting in an adjusted treatment effect of 101% for Lyft's bike-share integration.

7 Heterogeneity analysis

After reporting our headline results in Table 1 where non-subscribers significantly increase there use of bike-share after Lyft integrated bike-share in their ride-hailing app, we explore how the impact of treatment varies across a range of covariates. Investigating the heterogeneous impact of treatment will allow us to shed light on underlying mechanisms and circumstances that may prompt non-subscribers to choose bike-share over ride-hailing, and help design more effective policy.

We start by testing whether the treatment varies across working and non-working days. Non-working days are defined as either weekends or holidays.[10] Table 3 shows the result of a triple-difference estimation (see Equation 3) when the sample is split between working and non-working days. In our preferred specification (i.e., including weather controls), we find that the treatment increased non-subscriber ridership in NYC by 89%

[9] The estimation equation in this case is the same as Equation 2 for the split sample.

[10] Holidays are taken from the closing days calendar of the New York Stock exchange, as provided by the `timeDate` package for R. See https://geobosh.github.io/timeDateDoc/reference/holiday-NYSE.html (accessed 2024-02-23).

during holidays and weekends, while non-subscriber ridership almost doubled during working days with an increase of 164

This result may point towards the role of congestion in the choice of transport mode by users. Indeed, traffic is heavier during working days, and demand for ride-hailing higher. We hypothesize that by combining longer travel times and more expensive ride-hail rides, working days increase the relative attractiveness of bike-share, prompting marginal users to switch to bike-share while on the Lyft app looking for a ride-hail ride.

We explore this effect further by running another triple-difference estimation, focusing on working days split between rush hours and non-rush hours. The results are shown in Table 4. In line with the hypothesis that high congestion and demand for ride-hailing are positively associated with non-subscribers switching to bike-share, we find that NYC non-subscribers increase their bike-share ridership by 216% during rush-hour after treatment, while the increase outside rush hour is 120%. Taken together, these results suggest that bike-share acts as a substitute for ride-hailing in high congestion situations.

Next, we turn to the spatial distribution of the treatment effect by mapping where the introduction of bike-share on the Lyft app had a greater impact on non-subscriber ridership. We start by dividing the city in hexagons measuring 300 by 300 metres. Using the starting location of each trip, we then aggregate the number of trips originating from each hexagons for both subscribers and non-subscribers, for every day in 2018 and 2019. We then run a difference-in-differences model for non-subscribers trips separately for each cell, keeping the whole of Philadelphia as a control for every cell. We collect the estimates for each cell and map them in Figure 6.[11]

The map indicates that Lyft's integration of bike-share on its ride-hailing app increased non-subscriber trips differently across the city. In Manhattan, the southern tip of the island (where the Financial district is located), the eastern parts of Midtown and the south-east corner of Central Park have experienced the highest increases in trips made by non-subscribers due to the treatment. In the other boroughs, the north-east corner of Brooklyn shows the largest growth in non-subscriber ridership. We plan to continue exploring the spatial heterogeneity of treatment across several important dimensions such as access to other transport modes, and population and job density.

Finally, Figure 7 shows how the distribution of trip duration changed before and after the treatment in NYC for each user group. According to panel 7a, non-subscribers have increased the duration of their trips after the treatment, while the duration of subscribers' trips has remained largely constant. This may suggest that non-subscribers are switching to bike-share for trips normally taken using ride-hail, the latter being longer trips than what non-subscribers were accustomed to do prior to treatment.

[11] Because some stations opened after the treatment date, we only map cells that reported at least one trip prior to the treatment.

8 Substitution analysis

Lyft's integration of bike-share in their ride-hailing app poses the question of whether or not it induced fewer ride-hailing trips due to a substitution effect. To explore this question, we use Taxi & Limousine (TLC) data provided by nyc.gov (cite). TLC data records include time stamps for the origin and destinations of taxi and ride-hailing trips in NYC, allowing us to explore the potential for bike-share trips serving as a substitute for ride-hailing trips, after the treatment. However, the analysis is limited in causality for two main reasons. First, the data sets do not provide a unique user identifier to find exact users who switched from car-based rides to bike-based rides. Second, there is no comparable taxi or ride-hailing data to access in Philadelphia, leaving the analysis without a proper control city without the treatment.

To mitigate these limitations, we focus the study area to NYC, and compare taxi zone areas with bike-share stations to taxi zone areas without bike share stations, demonstrated in Figure 8. In areas with bike-share stations, users are exposed to the treatment effect, whereas in areas without bike-share stations, users are not given the choice of a bike-share ride (cite?) and therefore should not be affected by the treatment.

Using this framework, we develop an event study, identified in Equation 4, to investigate a substitution effect.

$$ln(Trips_{jwg}) = \alpha + \sum_{k=-2}^{-2} \beta_k \times Treat_j + \sum_{k=1}^{4} \beta_k \times Treat_j + \phi_j + \gamma_m + \varepsilon_{jwg}, \qquad (4)$$

where $ln(Trips_{jwg})$ is the number of ride-hailing trips taken on the app of company g in taxi zone j for week w in NYC. A taxi zone is either covered by bike-share stations ($Treat_j = 1$) or not ($Treat_j = 0$). The coefficients of interests are β_k and show the dynamic effects on ride-hail ridership in taxi zones covered by bike-share vs those not covered in the periods leading and following the integration of bike-share information on the Lyft app. The reference period is the month of the treatment. The event study is run separately for both Lyft ($g = lyft$) and Uber ($g = uber$).

Figure 9 plots the β_k from Equation 4 for periods before and after the treatment given by the dotted vertical line in May 2019.

While this event study suggests users exposed to the treatment are substituting their rides in favor of the Citi Bike share, there are two drawbacks to this analysis. First, the treatment and control areas are very different, given the treatment area corresponds with NYC's city center and the control area outside of it. These differences harm our ability to study the treatment area against a robust counterfactual, limiting our ability to achieve a causal substitution effect. Second, there is a risk of treatment spillovers and therefore a potential violation of the Stable Unit Treatment Value Assumption (SUTVA). Those who live outside of the treatment area may still become aware of the bike-share

service accessible via the Lyft app and decide to walk to the nearest bike-share station or alter their transportation strategy to be multi-modal and substitute a portion of their journey. These spillover effects may result in an under or over estimation of substitution occurring in this study.

8.1 Estimating environmental impact

Under the hypothesis where the treatment of Lyft's bike-share integration in their mobile app results in a causal increase of non-subscriber bike-share ridership by 110 %, we aim to estimate the effect on environmental impact. To do this, a number of parameters are gathered to use as rudimentary inputs into a calculation of CO_2 savings across a range of scenarios that represent a percent of car-based rides substituted at a ratio of 1% to 100%. The parameters, and the range of substitution scenarios, are displayed in Table 7.

The calculated CO_2 savings for each scenario are shown in Table 8, and are given in terms of CO_2 saved per week, per year, as an equivalency of yearly NYC-resident-emissions, and as a monetary savings value per week. We find that if 10% of the additional bike-share rides due to the treatment substituted a ride-hail ride, then 14 tons of CO_2 would be saved each week, equivalent to $2700 in savings per week using the EPA social cost of carbon (cite).

9 Discussion

Our DDD estimator clearly shows a large 122% increase of non-subscriber ridership in the Citi Bike network, pointing to the importance of a low-friction bike-share system that is easy to use, and integrated with other options for mobility in a city. This result agrees with the broader literature on how concepts such as perceived quality, perceived convenience, integration with other transit services, and overall system convenience increases ridership (Gao et al., 2019; Fishman et al., 2012; Hazen et al., 2015; Serna et al., 2019; Shaheen, Zhang, et al., 2011). Further, the treatment effect we find is larger than that of the relevant literature. Gao et al. (2019) finds that improving facilitating conditions, such as receiving instructions or being familiar with the rental technology resulted in a 30% higher intention to use bike-sharing systems. Hazen et al. (2015) found that an increase in perceived quality of public bicycles resulted in a 36% increase in adoption, and perceived convenience resulted in a 56% increase in bike-share adoption. However, the results of this paper are especially unique and reliable because they are purely empirical, establish causation, and are based off a detailed data set of true rider behavior rather than surveys or sentiment analysis.

9.1 Implications of corporate service aggregation

One contributing factor to the magnitude of our treatment effect is the benefit from Lyft operating as a partially integrated app where a single platform serves users with the

option of sourcing a car-based ride or finding and renting a public bicycle, demonstrated in Figure A2. Our results indicate that the concept of integration is beneficial to increasing ridership, likely through the effect of reduced switching costs when choosing between various options of transportation. However, there are various implications of a company, rather than public entity, owning and operating the aggregated service. When a company operates an aggregator-like app, there is a competitive interest in favoring their own services over others that are present in the total mobility landscape (Wolff, 2019).

In Lyft's case, their app only features their proprietary services, which is logical from a business perspective, but results in transit inefficiencies for the public who would otherwise benefit from a comprehensive aggregator app providing multimodal planning (Wolff, 2019). Further, even when using a completely aggregated mobility services app, such as Citymapper, users who wish to view pricing estimates and trip information related to private ride-hailing companies encounter a walled garden, where they are forced to open the external proprietary app to do so (CityMapper, 2024). These siloed mobility systems create inefficiencies for the producer and the consumer; Lyft forgoes additional trips because users may not be willing to incur the additional switching costs necessary to create a journey that includes ride-hailing transportation, and users lack a more transparent set of mobility options when presented with an optimal route for their trip.

One method for reaping the benefits of aggregator apps, but without the risks and inefficiencies that come with corporate ownership, is to introduce a mid-layer that is operated by a public entity or regulator (Wolff, 2019; Kamargianni and Matyas, 2017). A mid-layer acts as a data intermediary between private operators, such as Lyft, and aggregators, such as Citymapper (Wolff, 2019). Data from the operators is sent to the mid-layer, which then acts as a central point of data access for aggregators to reference, preventing unnecessary communication with each individual operator for trip information (Wolff, 2019). The mid-layer is best operated by a public entity because they can ensure it is standardized, and that data is shared in a universal format to facilitate interoperability among all parties (Kamargianni and Matyas, 2017).

Further, a public entity operating the mid-layer can result in a regulated and better managed urban mobility system that not only benefits the public without sacrificing fairness in the marketplace, but also allows for continuous improvements in efficiency and sustainability (Wolff, 2019; Kamargianni and Matyas, 2017). This discussion serves the purpose of advocating for the integration of mobility services, as Lyft made through their acquisition, but not without a careful implementation that considers transparency and fairness.

9.2 Limitations

While this paper provides important and substantial results, it would be incomplete without a discussion addressing any potential limitations. First, both Indego and Citi

Bike fleets featured electric bicycles (e-bikes) for users to rent in 2019. Because of the recent popularity and growth of e-bikes (Schleinitz et al., 2017; He et al., 2019), it is possible that ridership is influenced by the availability of them in each city's fleet. To maintain a reliable counterfactual, we attempt to remove all e-bike trips from our analysis, however, Citi Bike fails to provide an e-bike identifier in their 2019 data, whereas Indego does provide one. Indego's e-bike fleet totals to 10, out of approximately 1500 total bikes (Caspi, 2023). This data was removed from the dataset. In early 2019 Citi Bike had an e-bike fleet of roughly 1,000 bikes (Pager, 2019), relative to a total fleet size of 10,000. However, due to mechanical failures, Citi Bike had to recall their e-bike fleet in April 2019, and did not re-launch e-bikes until 2020, after our study period. Citi Bike does not provide an indicator in the data set to filter out e-bike trips, therefore ridership data from January to April 2019 may be partially inflated compared to the post-period. However, this does not substantially affect ridership data, or threaten the parallel trends assumption, as inspected visually in Figure 2 and statistically through a series of robustness tests in Section 5. This may be due to Citi Bike replacing the recalled e-bikes with traditional pedal bikes while the mechanical issue was investigated, mitigating any significant disruption to the system (Hawkins, 2019).

Secondly, this paper may be exposed to confounding factors related to improvement in bicycle infrastructure and its ability to increase bicycle use through efforts such as added or improved bike lanes and public bike re-balancing efforts. For example, throughout 2019, 15 streets in Manhattan contained either newly built or improved bike lanes (NYCDOT, 2023). There is evidence that people are willing to take 2-4x longer trips by bicycle if they can use a bike trail or bike lane for their journey, and that every additional kilometer of bike lane within half of a mile to a bike-share station can result in an average of 3.5 more rides per day (Hunt and Abraham, 2007; Buck and Buehler, 2012). While our DDD methodology aims to remove city-specific time-variant bias, such as bicycle infrastructure changes, it is possible that the effects of these factors differ between subscribers and non-subscribers, in which the third difference in our model would not remove all endogenous effects. Therefore, we can interpret these biases as reduced but not entirely removed. Additionally, some bike stations have issues with being unbalanced, in which large flows to and from different areas, like during commute hours, result in users being met with an empty bike station or unable to return their bike because a station is at capacity (Freund et al., 2019; Corcoran et al., 2014). To re-balance stations around the city, bike-share companies use large vans to transport and redistribute the bikes accordingly (Freund et al., 2019; Citi Bike, 2019c). Eventually, companies such as Lyft started to implement crowd-sourced rebalancing efforts, termed "Bike Angels", where people are compensated for riding bikes to stations that required re-balancing (Mestel, 2022; Lyft, 2023; Freund et al., 2019; Citi Bike, 2019c). Re-balancing efforts can influence ridership trends through improved access to the bike system (Freund et al., 2019). While Citi Bike does provide a monthly count of rebalanced bikes in 2019, Indego

does not, and therefore limits our ability to control for these efforts. Similar to bike lane expansion, our DDD methodology mitigates some bias from re-balancing efforts, but not entirely if the bias effects subscriber groups differently across time.

Third, it is possible that the changes Lyft made to the Citi Bike system caused non-subscriber users to become subscribers, or vice versa. This is a concern because a time-variant change in the composition of our subscriber and non-subscriber groups due to the treatment threatens the parallel trends assumption and can lead to an over or under-estimation of the treatment effect. To control for these effects, the data would need a unique identifier for each rider over time, a component it does not currently feature. It is unlikely for subscribers to become non-subscribers due to the treatment, given annual subscriptions are purchased in full once a year. However, one could argue that the treatment led to a higher rate of trialability among non-subscriber, thus encouraging them to incorporate public bikes into their mobility preferences to the point of switching to an annual subscription.

Lastly, our treatment effect is limited in detail due to Lyft implementing a broad set of changes at once with the intention of making the Citi Bike system easier to use. Specifically, our results are measuring the joint effect of changes to how a bike is rented, how it is unlocked, and the aggregation of Lyft services. Ideally, one could research how each isolated change influenced ridership outcomes, but this would require the changes to have been introduced subsequently and then measured in effect individually. Further, the success of these features together likely benefits from the prior success of Lyft and its widespread app availability before they had acquired Motivate and integrated their services. While Lyft clearly found success in the task of improving the ease-of-use of the system, there is certainly a unique advantage to existing as a familiar service and operating in a related transit market. One concept this advantage is exemplified by is mergers and acquisitions, where a firm such as Lyft can grow their company, offer users a better value proposition, and increase their competitive advantage through the purchase and integration of another company (Čirjevskis, 2019). These benefits are a logical path towards a lower economy of scope (Panzar and Willig, 1981), where Lyft can provide multiple transportation services for a lower marginal cost, and users can benefit from reduced search costs and increased transit efficiencies. An additional concept supporting this effect is Lyft's ability to gain from a second mover strategy regarding the integration of public bicycles into their platform. Using technological features from its successful ride-hailing product, Lyft was able to improve the bike-sharing experience relative to other systems and leverage informational spillovers from users having already engaged with their product in the past, resulting in a higher rate of adoption (Hoppe, 2002). The effect Lyft received from these tactics individually is not something we can easily quantify in the scope of this paper, so our results are best interpreted as reflecting an aggregate response in ridership to a group of key system improvements conditional on a higher likelihood of adoption given Lyft's historical success and strategy.

10 Conclusion

Our study contributes to the environmental literature by quantifying the effects of ride-hailing integration on transportation-related CO_2 emissions and local pollution. Transportation accounts for 20%–40% of total emissions in many major cities (Isik et al., 2021). Prior research has examined policies such as fuel economy standards (Knittel and Davis, 2019; Jacobsen et al., 2023) and low-emission zones (Wolff, 2014) in reducing urban air pollution. Our findings suggest that integrating bike-sharing with ride-hailing platforms can encourage a shift toward cycling, potentially lowering the environmental footprint of urban transportation.

This paper provides the first empirical evidence on how integrating bike-sharing services into a major ride-hailing platform affects ridership and modal substitution The motivation to research the underlying characteristics for what increases public bike-share adoption is demonstrated by a diverse set of private and public benefits. Our research provides valuable insight into the factors that increase user adoption, and the magnitude of increased ridership from them. A DDD model is employed to uncover the total causal effect of technological improvement, the aggregation of transportation service options, and the simplification of a bike-share rental system on Citi Bike ridership. The treatment results in a 122% increase in non-subscriber ridership, equating to an approximate increase of 13% with respect to total Citi Bike ridership.

In response to findings from similar studies in the bike-share and mobility literature, this result is significant because it offers a causal effect that is calculated using data from real public cycling behavior, rather than survey data. Additionally, it shows that results of similar studies in the public bikeshare literature may have been underestimated. Further, there is strong external validity to our results given the similarity of how public bike-share systems operate within the United States and globally. For example, in 2023 the London Santander bicycle system still operates almost identically (Santander Cycles, 2023) to the Citi Bike system before Lyft had implemented any changes, indicating the opportunity for large potential gains in ridership and mobility. This paper makes a series of other valuable contributions in areas such as the technology acceptance model in transportation and the benefits of multi-modal aggregations. However, there are potential limitations to this study including Citi Bikes having electric bicycles in their fleet, unobserved changes to bicycle infrastructure, and the inability to separate out individual treatment effects from Lyft's collective launch of several features that improved the bike-share system. These limitations do not appear to significantly threaten the validity of our results, but they do provide topics to be considered and improved upon in further research.

With transportation being responsible for roughly 25% of all greenhouse gas emissions (UN Environment Programme, 2020), it is logical that city planners are searching for ways to optimize their greater mobility strategy and operate a more efficient system. Bike-sharing can help with this initiative both by complementing existing transit options

and replacing some carbon-intensive ones (Martin and Shaheen, 2014). Further, this paper demonstrates how cities can benefit from adoption of the TAM as they integrate more technology into transportation solutions as a strategy for sustainably growing their mobility system. Adoption of a new or improved service not only requires for it to be built, but to have been built in a user-friendly way that is easy to trial and encourages repeated use.

Importantly, technological integration, demonstrated by Lyft aggregating ride-hailing and bicycle services into their platform, must be carefully operated in a way that reaps all associated benefits, but without granting preference to corporations and risking unfair treatment of city residents. This emphasizes the need for close coordination between private and public entities as local transportation policy is developed.

Evidently, there are a suite of effective options available to cities and companies who wish to encourage a stronger adoption of public bicycles, making it sensible to employ them. This case study involving Lyft and the Citi Bike system provides a pathway of improvement, and evidence of success, for other cities domestic and international that want to increase bike- share ridership. However, it is important to consider that bike-sharing is only one form of transportation that operates within a broader ecosystem of mobility services. Therefore, research and city planners should not only continue developing methods to optimize each service individually, but to also work towards an understanding of how all forms of transportation might interact with each other. As comprehensive improvements are made, cities can provide a more efficient and sustainable transportation network for future generations to enjoy.

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11 Tables and figures

Table 1: Bike-share — difference-in-differences and triple differences

	log(trips)			
	Diff-in-diff		Triple diff	
	(1)	(2)	(3)	(4)
Treated × Post-period	0.1317***	0.1233***	0.0532**	0.0387
	(0.0226)	(0.0293)	(0.0207)	(0.0320)
Treated	3.3640***	3.4577***	3.4023***	3.5424***
	(0.0181)	(0.0279)	(0.0173)	(0.0291)
Post-period	-0.0209	-0.0482	-0.1248**	-0.1596***
	(0.0360)	(0.0369)	(0.0558)	(0.0601)
Treated × Post-period × Non-subscribers			0.7992***	0.7992***
			(0.0666)	(0.0666)
Treated × Non-subscribers			-0.2851***	-0.2851***
			(0.0428)	(0.0428)
Post-period × Non-subscribers			-0.1047	-0.1047
			(0.1287)	(0.1287)
Non-subscribers			-2.2606***	-2.2606***
			(0.0647)	(0.0647)
Weather controls		Yes		Yes
Month FE (12)	Yes	Yes	Yes	Yes
Observations	1,460	1,460	2,920	2,920
Adjusted R^2	0.952	0.971	0.913	0.935
Within Adjusted R^2	0.950	0.969	0.906	0.930
RMSE	0.390	0.305	0.661	0.571

Notes: Standard errors clustered by year-week identifiers (e.g., 2018w5). Significance codes: *: 0.1, **: 0.05, ***: 0.01. Estimated using a daily panel of trips. *Weather controls* include average temperature, precipitations, snow depth and average wind speed. The sample period is 2018–2019. The DD model (column 1 and 2) estimates the impact of treatment on all trips, i.e., for both subscribers and non-subscribers, as described in Equation 2. The DDD model (column 3 and 4) estimates Equation 3. *Subscribers* are bike-share riders who subscribed to either a monthly or annual plan — all the other users are considered *Non-subscribers*.

Table 2: Bike-share — difference-in-differences for subscribers and non-subscribers

	log(trips)			
	Subscribers		Non-subscribers	
	(1)	(2)	(3)	(4)
Treated × Post-period	0.0532**	0.0454*	0.8524***	0.8313***
	(0.0208)	(0.0272)	(0.0747)	(0.0818)
Treated	3.4023***	3.4863***	3.1172***	3.3134***
	(0.0173)	(0.0278)	(0.0476)	(0.0508)
Post-period	0.0091	-0.0158	-0.3634***	-0.4082***
	(0.0373)	(0.0385)	(0.0738)	(0.0696)
Weather controls		Yes		Yes
Month FE (12)	Yes	Yes	Yes	Yes
Observations	1,460	1,460	1,460	1,460
Adjusted R^2	0.949	0.964	0.857	0.905
Within Adjusted R^2	0.947	0.963	0.830	0.886
RMSE	0.404	0.337	0.770	0.628

Notes: Standard errors clustered by year-week identifiers (e.g., 2018w5). Significance codes: *: 0.1, **: 0.05, ***: 0.01. Estimated using a daily panel of trips. The estimating equation is Equation 2, except the sample was split between subscribers and non-subscribers. *Weather controls* include average temperature, precipitations, snow depth and average wind speed. *Subscribers* are bike-share riders who subscribed to either a monthly or annual plan — all the other users are considered *Non-subscribers*. The sample period is 2018–2019.

Table 3: Bike-share — triple differences for non-working and working days

	asinh(trips)			
	Non-working day		Working day	
	(1)	(2)	(3)	(4)
Treated × Post-period × Non-subscribers	0.6384***	0.6384***	0.8703***	0.8703***
	(0.0729)	(0.0731)	(0.0773)	(0.0774)
Treated × Post-period	0.0197	0.0019	0.0686***	0.0562*
	(0.0284)	(0.0509)	(0.0207)	(0.0312)
Treated × Non-subscribers	-0.4684***	-0.4684***	-0.2033***	-0.2033***
	(0.0481)	(0.0482)	(0.0509)	(0.0509)
Post-period × Non-subscribers	0.0416	0.0416	-0.1661	-0.1661
	(0.1380)	(0.1383)	(0.1323)	(0.1324)
Treated	3.5162***	3.6560***	3.3510***	3.4885***
	(0.0214)	(0.0389)	(0.0179)	(0.0302)
Post-period	-0.0593	-0.1605**	-0.1562***	-0.1663***
	(0.0798)	(0.0724)	(0.0567)	(0.0607)
Non-subscribers	-1.3786***	-1.3786***	-2.6566***	-2.6566***
	(0.0809)	(0.0811)	(0.0683)	(0.0683)
Weather controls		Yes		Yes
Month FE (12)	Yes	Yes	Yes	Yes
Observations	904	904	2,016	2,016
Adjusted R^2	0.902	0.937	0.939	0.956
Within Adjusted R^2	0.893	0.931	0.935	0.954
RMSE	0.641	0.513	0.569	0.482

Notes: Standard errors clustered by year-week identifiers (e.g., 2018w5). Significance codes: *: 0.1, **: 0.05, ***: 0.01. *Weather controls* include average temperature, precipitations, snow depth and average wind speed. Estimated using a daily panel of trips. The outcome variable is the inverse hyperbolic sine of the number of trips, a transformation comparable to the natural logarithm but that can accommodate zero values (MacKinnon and Magee, 1990). Column 1 and 2 estimate a triple-difference model for non-working days (weekends and holidays), column 2 and 3 for working days. The estimated model is described in Equation 3. The sample period is 2018–2019.

Table 4: Bike-share — triple differences for rush-hours and non-rush-hours during working days

	asinh(trips)			
	Outside rush-hour		During rush-hour	
	(1)	(2)	(3)	(4)
Treated × Post-period × Non-subscribers	0.7899***	0.7899***	1.1515***	1.1515***
	(0.0768)	(0.0768)	(0.0953)	(0.0954)
Treated × Post-period	0.0762***	0.0635**	0.0534**	0.0416
	(0.0213)	(0.0319)	(0.0240)	(0.0338)
Treated × Non-subscribers	-0.1710***	-0.1710***	-0.2927***	-0.2927***
	(0.0497)	(0.0497)	(0.0649)	(0.0650)
Post-period × Non-subscribers	-0.1395	-0.1395	-0.2778*	-0.2778*
	(0.1340)	(0.1341)	(0.1412)	(0.1414)
Treated	3.3682***	3.5095***	3.3233***	3.4519***
	(0.0180)	(0.0308)	(0.0191)	(0.0319)
Post-period	-0.1619***	-0.1722***	-0.1395**	-0.1495**
	(0.0545)	(0.0589)	(0.0693)	(0.0725)
Non-subscribers	-2.4496***	-2.4496***	-3.1749***	-3.1749***
	(0.0708)	(0.0708)	(0.0677)	(0.0678)
Weather controls		Yes		Yes
Month FE (12)	Yes	Yes	Yes	Yes
Observations	2,016	2,016	2,016	2,016
Adjusted R^2	0.934	0.952	0.939	0.955
Within Adjusted R^2	0.930	0.949	0.936	0.952
RMSE	0.580	0.495	0.612	0.527

Notes: Standard errors clustered by year-week identifiers (e.g., 2018w5). Significance codes: *: 0.1, **: 0.05, ***: 0.01. Estimated using a daily panel of trips. *Weather controls* include average temperature, precipitations, snow depth and average wind speed. The outcome variable is the inverse hyperbolic sine of the number of trips, a transformation comparable to the natural logarithm but that can accommodate zero values (MacKinnon and Magee, 1990). The sample is restricted to working days (i.e., excluding weekends and holidays) and estimated using Equation 3. *Rush-hour* are defined as hours from 7 to 9AM and from 5 to 7PM — *Outside rush-hour* are all other hours. The sample period is 2018–2019.

Table 5: Bike-share — triple differences, placebo post-period vs real post-period

	log(trips)			
	Triple diff			
	Real post-period		Placebo post-period	
	(1)	(2)	(3)	(4)
Treated × Post-period × Non-subscribers	0.7992***	0.7992***		
	(0.0666)	(0.0666)		
Treated × Post-period placebo × Non-subscribers			0.1929***	0.1929***
			(0.0660)	(0.0663)
Treated × Post-period	0.0532**	0.0387		
	(0.0207)	(0.0320)		
Treated × Post-period placebo			-0.0944***	-0.0466
			(0.0246)	(0.0518)
Treated × Non-subscribers	-0.2851***	-0.2851***	-0.2711***	-0.2711***
	(0.0428)	(0.0428)	(0.0501)	(0.0503)
Post-period × Non-subscribers	-0.1047	-0.1047		
	(0.1287)	(0.1287)		
Post-period placebo × Non-subscribers			0.5352***	0.5352***
			(0.1570)	(0.1576)
Post-period	-0.1248**	-0.1596***		
	(0.0558)	(0.0601)		
Post-period placebo			-0.5796***	-0.3542***
			(0.0638)	(0.0939)
Treated	3.4023***	3.5424***	3.5798***	3.8175***
	(0.0173)	(0.0291)	(0.0230)	(0.0334)
Non-subscribers	-2.2606***	-2.2606***	-2.4679***	-2.4679***
	(0.0647)	(0.0647)	(0.1497)	(0.1502)
Weather controls		Yes		Yes
Month FE (12)	Yes	Yes		
Year-week FE (21)			Yes	Yes
Observations	2,920	2,920	564	564
Adjusted R^2	0.913	0.935	0.916	0.948
Within Adjusted R^2	0.906	0.930	0.913	0.946
RMSE	0.661	0.571	0.655	0.514

Notes: Standard errors clustered by year-week identifiers (e.g., 2018w5). Significance codes: *: 0.1, **: 0.05, ***: 0.01. Estimated using a daily panel of trips. *Weather controls* include average temperature, precipitations, snow depth and average wind speed. The model estimates Equation 3, except the fixed effects are at the week level. For Columns 1 and 2, the post-period is May 7, 2019, when Indego changed their pricing scheme and the sample period runs until May 21, 2019, a day before Citibike information was added to the Lyft app. Columns 3 and 4 are the same as in Table 1 and are reproduced here for convenience. *Subscribers* are bike-share riders who subscribed to either a monthly or annual plan — all the other users are considered *Non-subscribers*. .

Table 6: Ride-hailing — double and triple differences, Lyft vs Uber, outside bike-share vs inside bike-share area

	asinh(trip_count)		
	Diff-in-diff		Triple diff
	Lyft	Uber	Both
	(1)	(2)	(3)
Post-period × PU in bike area	-0.1055***	-0.0756***	-0.0762***
	(0.0192)	(0.0221)	(0.0221)
Post-period × PU in bike area × Lyft			-0.0290**
			(0.0110)
Post-period × Lyft			0.1393***
			(0.0291)
PU in bike area × Lyft			0.4194***
			(0.0092)
Post-period	0.0992***	-0.0246	-0.0333
	(0.0228)	(0.0206)	(0.0206)
Year-month FE (9)	Yes	Yes	Yes
Pickup zone FE (260)	Yes	Yes	Yes
Ride-hail company FE (2)			Yes
Observations	10,037	10,066	20,103
Adjusted R^2	0.985	0.987	0.979
Within Adjusted R^2	0.021	0.013	0.173
RMSE	0.182	0.167	0.230

Notes: Standard errors clustered by year-week identifiers (e.g., 2018w5). Significance codes: *: 0.1, **: 0.05, ***: 0.01. Column 1 and 2 perform a separate difference-in-differences estimation on the ridership of Lyft and Uber following the integration of bike-share information on the Lyft app, comparing ridership inside the bike-share area (**P**ick **U**p location in Bike-Share area) with ridership outside the bike-share area. Column 3 combine 1 and 2 in a triple difference framework, with the ride-hailing company as the third difference. Pick-up areas are taxi zones (see Fig 8. Standard errors clustered by year-week identifiers (e.g., 2018w5).

Table 7: Environmental impact parameters

Parameter	**Value**	**Source**
Additional non-subscriber bike-share trips per week (count)	42,000.00	From analysis
Ratio of substitution from Lyft trips (%)	[1, 0.5, 0.1, 0.01]	Arbitrary
Average weekly Lyft trips in bike-share areas pre-treatment (count)	627,902.50	TLC data
Average Lyft trip distance in bike-share taxi zones (mi)	7.71	TLC data
Additional distance between trips factor (%)	1.2	Arbitrary
Share of gas vehicles in FHV fleet (%)	0.90	TLC Factbook
Average CO_2 emissions per mile (kg)	0.40	EPA
Average emissions by NYC residents per year (tons)	11.00	NYC Climate
Social cost of CO_2 per ton ($)	193	EPA

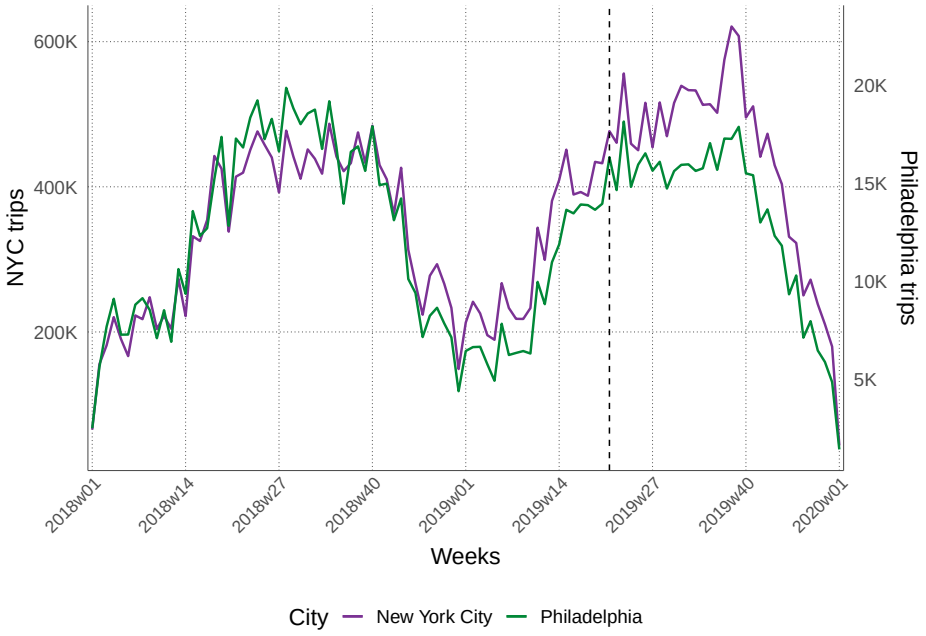
Notes: Table 5 presents key environmental impact parameters used to calculate potential CO_2 savings, including estimates of bike-share trips and distances, substitution ratios from Lyft trips, and CO_2 emissions factors. Some values are based on analytical assumptions.

Table 8: CO_2 savings across scenarios

	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Ratio new bike trips subst. Lyft trips (%)	1.00	0.50	0.10	0.01
Share of weekly Lyft trips substituted (%)	6.69%	3.34%	0.67%	0.07%
CO_2 saved per week (tons)	139.89	69.95	13.99	1.40
CO_2 saved per year (tons)	7,274.29	3,637.15	727.43	72.74
Resident-equiv. CO_2 saved per year (count)	661.30	330.60	66.10	6.60
Monetary value of CO_2 saved per week ($)	26,998.82	13,499.41	2,699.88	269.99

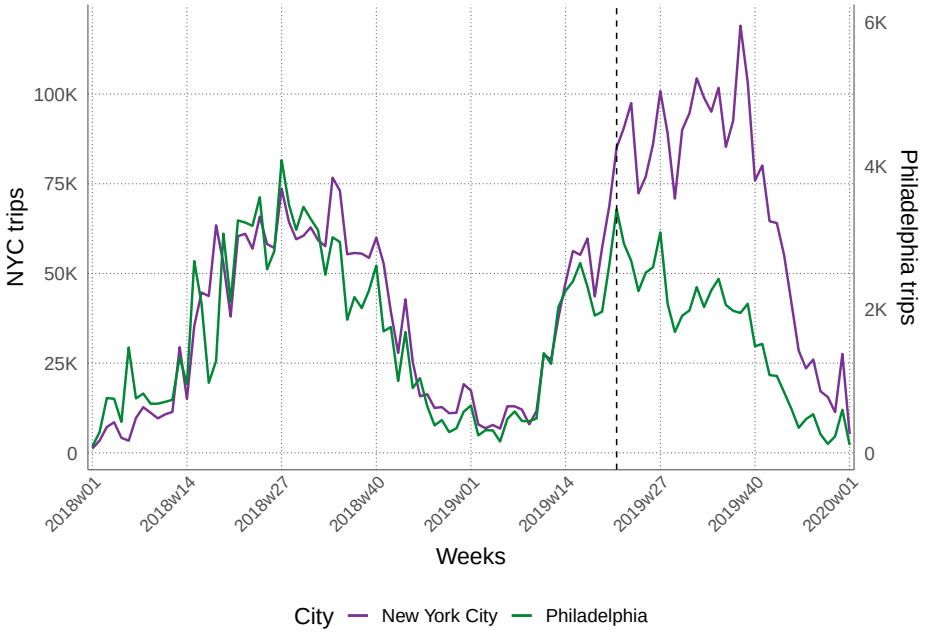
Notes: Table 6 reports estimated CO_2 savings across four substitution scenarios, varying the percentage of Lyft trips replaced by bike-share trips. Higher substitution rates lead to greater weekly and annual CO_2 reductions, with corresponding monetary valuations based on the social cost of carbon.

Figure 1: Bike-share trips by city



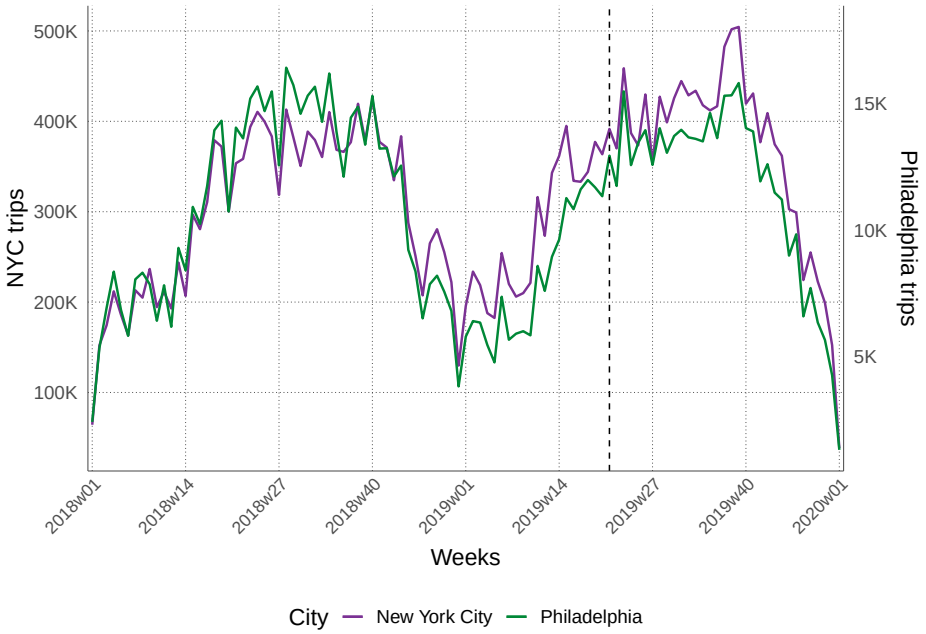
Notes: Weekly sum of all trips, by all user types (subscribers and non-subscribers) for NYC (purple line, left scale) and Philadelphia (green line, right scale) from the start of 2018 to the end of 2019. The dotted line represents the treatment date (May 22, 2019) when Lyft integrated bike-share into its ride-hailing app.

Figure 2: Trips by non-subscribers



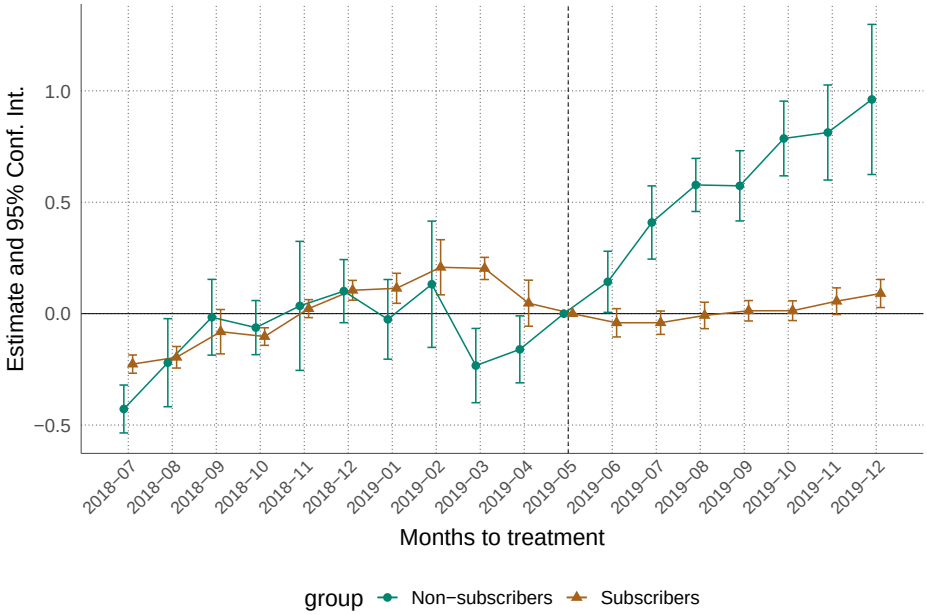
Notes: Weekly sum of trips made by non-subscribers in NYC (purple line, left scale) and Philadelphia (green line, right scale) from the start of 2018 to the end of 2019. The dotted vertical line represents the treatment date (May 22, 2019) when Lyft integrated bike-share in its ride-hailing app.

Figure 3: Trips by subscribers



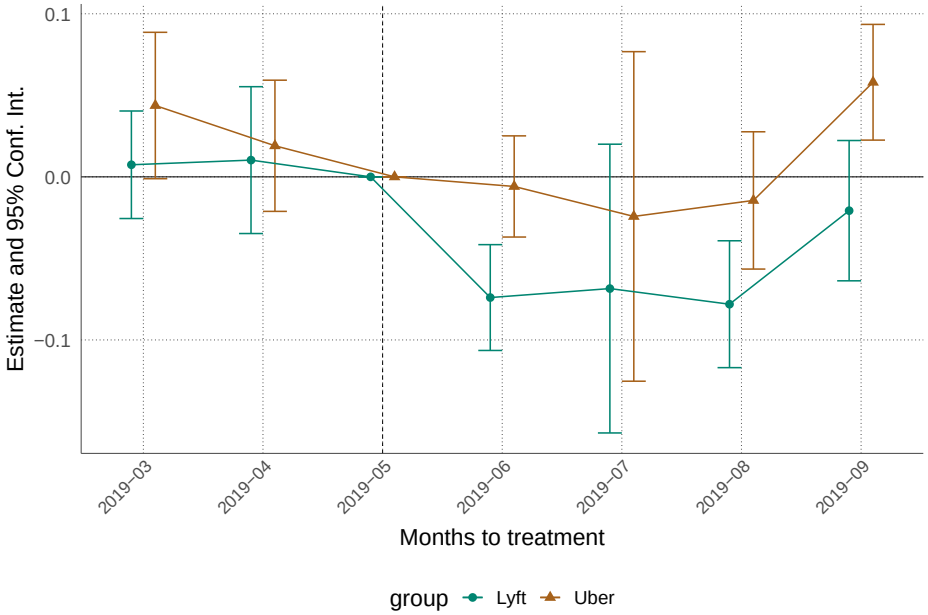
Notes: Weekly sum of trips made by subscribers in NYC (purple line, left scale) and Philadelphia (green line, right scale) from the start of 2018 to the end of 2019. The dotted vertical line represents the treatment date (May 22, 2019) when Lyft integrated bike-share in its ride-hailing app.

Figure 4: Event study, non-subscribers vs subscribers



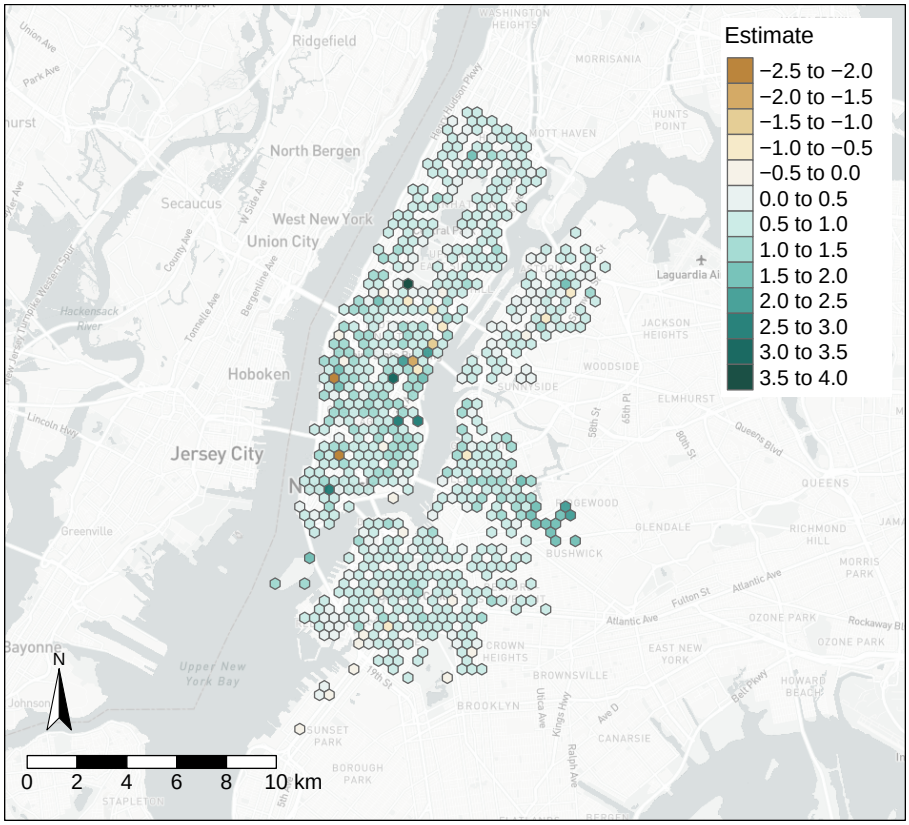
Notes: Plots the coefficients estimated by Equation 1, i.e., the difference in ridership between NYC and Philadelphia in the months leading to and following treatment (dotted vertical line). The green line (circle symbols) plots point estimates for the difference in ridership for non-subscribers, while the orange (triangle symbols) plots point estimates for subscribers. The vertical lines show 95% confidence intervals. Prior to treatment, there are no statistically significant differences in ridership of both groups between the treated (NYC) and control (Philadelphia) cities. After treatment, non-subscriber ridership increases in NYC compared to Philadelphia (green line, circles), while the difference in subscriber ridership across cities remains constant (orange line, triangles). Standard errors clustered by year-week identifiers (e.g., 2018w5).

Figure 5: Event study, Lyft vs Uber, bike-share area vs outside bike-share area



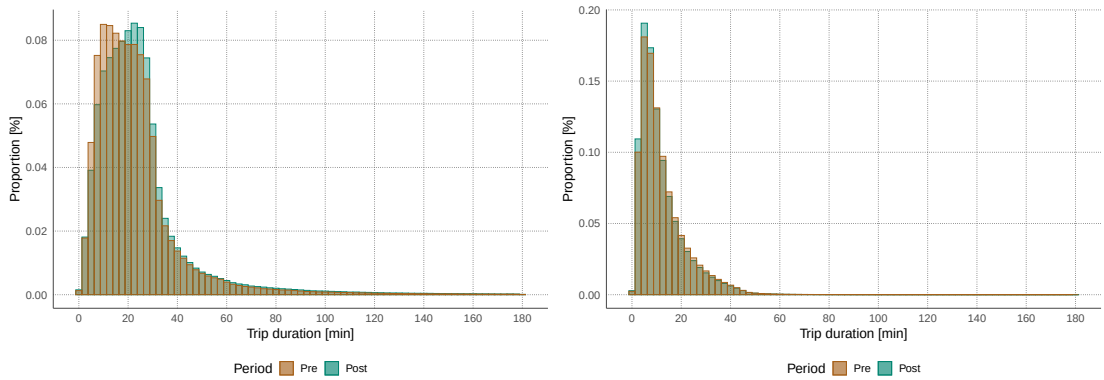
Notes: Plots the coefficients estimated by Equation 1, i.e., the difference in ridership between bike-share and non-bike-share in the months leading to and following treatment (dotted vertical line). The green line (circle symbols) plots point estimates for the difference in ridership for Lyft, while the orange (triangle symbols) plots point estimates for Uber. The vertical lines show 95% confidence intervals. Prior to treatment, there are no statistically significant differences in ridership of both groups between the treated (taxi zones with bike-share stations) and control (taxi zones without bike-share stations) cities. After treatment, Lyft ridership decreases in bike-share areas compared to non-bike-share areas (green line, circles), while the difference in Uber ridership across the city remains constant (orange line, triangles). Standard errors clustered by year-week identifiers (e.g., 2018w5).

Figure 6: Map of treatment effects



Notes: Plots the estimated treatment effect for a given cell. Blue colors indicate positive treatment effects, while yellow ones are negative. The estimated DD model is given by Equation 2, but for the non-subscribers sub-sample, using a daily panel summing all departing trips within a cell. For each regression, a given cell is selected and all the others dropped — this is repeated for every cell. The Philadelphia observations are kept as is. The DD coefficient, representing the impact of treatment on non-subscribers, is then plotted for all cells that reported at least one trip prior to treatment (to avoid plotting cells where stations came online after treatment).

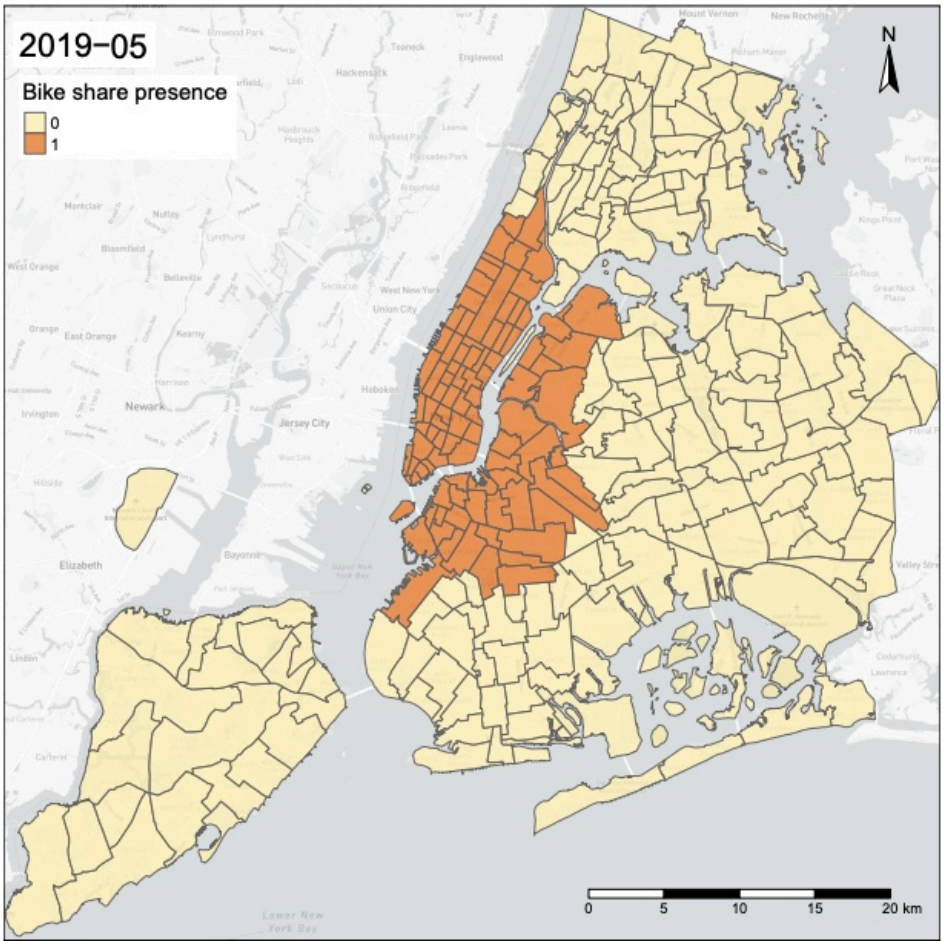
Figure 7: Distribution of trip duration in NYC, pre and post treatment



(a) Non-subscribers (b) Subscribers

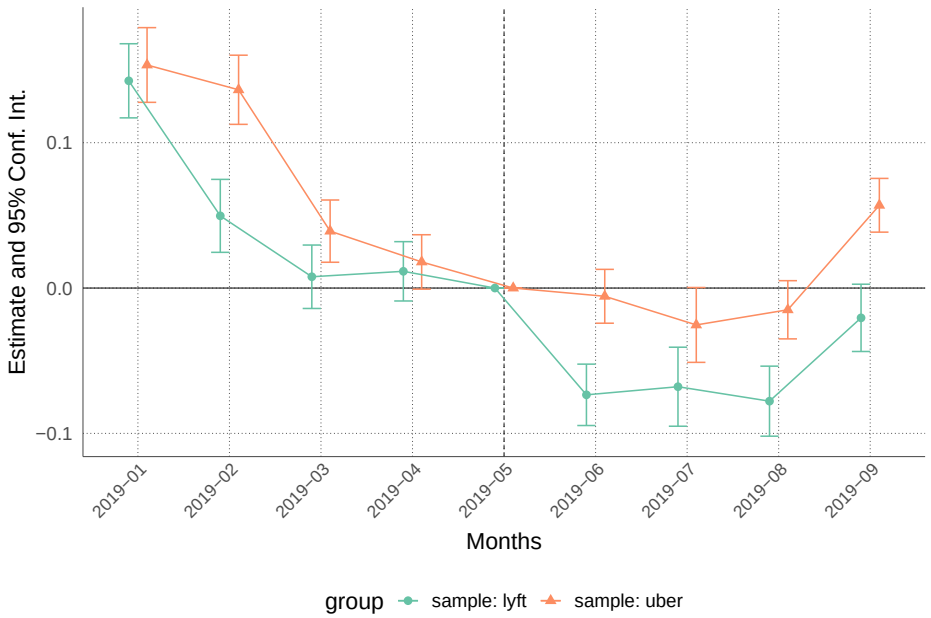
Notes: Shows the histogram of trip duration by user group (panel (a) for non-subscribers, panel (b) for subscribers) and period (yellow, pre-treatment; blue, post-treatment). The distribution of trip duration changes for non-subscribers from pre to to post, while it remains constant for subscribers.

Figure 8: Bicycle-share treatment by taxi zones



Notes: Plots the presence of NYC Citi Bike bike-share by taxi zone during May 2019. Taxi zones where bike-share was present are indicated by 1 (orange) and zones where bike-share was not present are indicated by 0 (yellow).

Figure 9: Car-based ridership substitution event study



Notes: Plots the coefficients estimated by Equation 4 (i.e., the difference in Lyft and Uber ride-hailing trips between NYC taxi zones with bike-share stations and without bike-share stations) in the months before and after the bike-share treatment in May 2019 (dotted vertical line). The green line (circle symbols) plots point estimates for the difference in car-based ridership for Lyft users, while the orange line (triangle symbols) plots estimates for Uber users. The vertical lines show 95% confidence intervals. In the period after treatment, there is some suggestive evidence that car-based ridership decreases for Uber compared to Lyft.

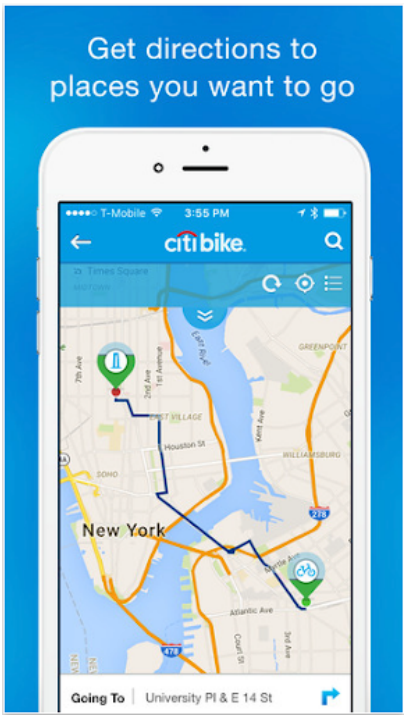
A Bike rental procedure

A.1 Citi Bike

Figure A1: Citi Bike mobile application interface pre-treatment



(a) Map of Citi Bike stations and the number of bikes available.



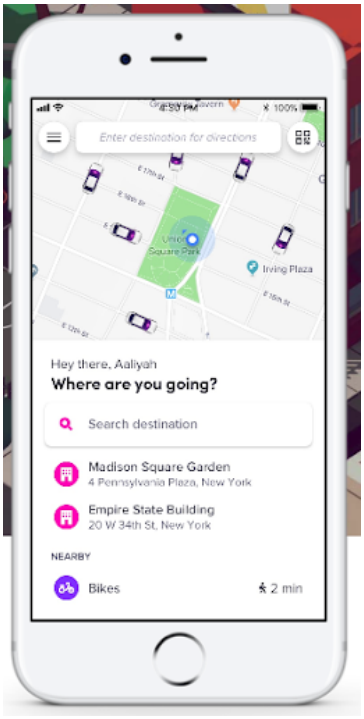
(b) Route mapping capabilities.

Notes: These are screenshots of the Citi Bike mobile app prior to integration of bike-share in Lyft's ride-hailing app. Note that after treatment, the Citi Bike app continued to exists.

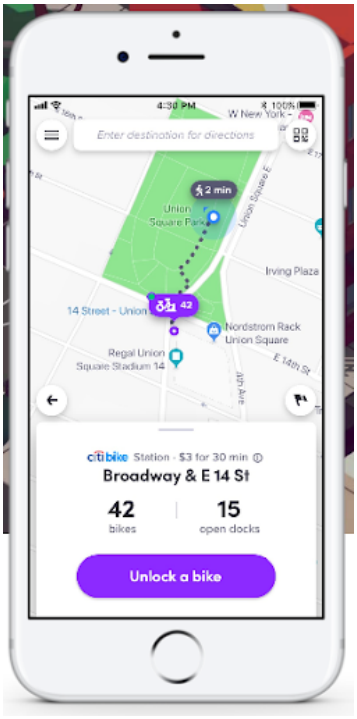
The procedure to rent a Citi Bike pre-acquisition could be conducted in two ways. One option is to rent a bike through a physical kiosk at a Citi Bike station. Instructions by Citi Bike are as follows (Citi Bike, 2016):

- Push the button on the kiosk to wake up the screen
- Press the "Rent a bike" button on the kiosk screen
- Insert your credit or debit card
- Choose how many bikes you'd like — up to 4
- Select the type of pass you'd like
- Print your ride code, which you'll use to unlock your bike(s)
- Pick out your bike(s) — skip any docks with a red light

Figure A2: Lyft mobile application interface post-treatment



(a) One app, two options: ride-hail or bike-share



(b) Route to a bike station and the number of bikes available

Notes: The landing page of Lyft's ride-hailing app as it appeared after the integration of bike-share. Users are now proposed a bike-share ride alongside ride-hail rides. This change in Lyft's ride-hail app provides its users with an increased awareness of their mobility options, and, for those who choose to bike-share, makes the switch to bike-share seamless since the user can user their Lyft account to book and pay for the bike-share ride.

- Type the code into the keypad on the bike dock(s) within 5 minutes
- When the light on the dock turns green, lift the bike by the seat to unlock it

The second option is through the Citi Bike mobile app, where users can find various docking stations, the number of available bikes at each, and purchase a pass. The steps to purchase a pass are similar to the steps required at a kiosk, as follows (Citi Bike, 2020b):

- Download the app
- Click Get a Pass
- Select the pass or membership you want to purchase
- Once you've purchased your pass, go to the Citi Bike station you'd like to use and tap on the station icon in the map
- Select "Unlock a bike" and a 5-digit ride code will appear on the screen

- Type the 5-digit ride code into any dock with an available bike to unlock the bike
- When the light on the dock turns green, lift the bike by the seat to remove it from the dock

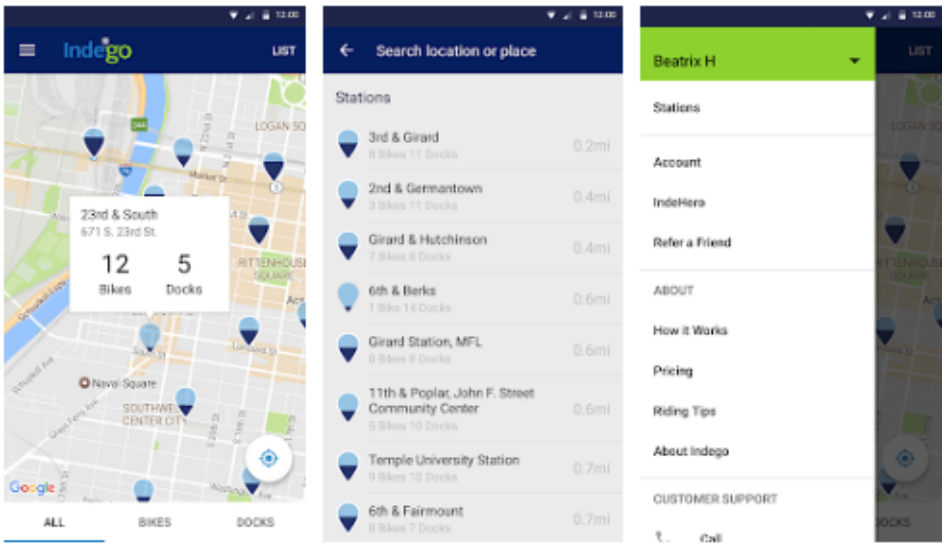
A.2 Indego

An Indego bike rental pass can be purchased online, at a kiosk, or through the Indego app, and unlocked either through a physical Kiosk, or via the Indego mobile app. The mobile app unlock feature instructs the user as follows (Indego, 2023a):

- Find the nearest station on the map
- While logged into your account, tap "unlock bike"
- Tap the dock number for the bike you want to check out

The steps are similar when using a pass purchased from a kiosk, except the user is required to produce a debit or credit card for payment before unlocking the bike. To access a bike from a pass purchased online, a user is required to find a station with a touch-screen kiosk and look up their account phone number to then proceed to unlocking the desired bike (Indego, 2019c). Lastly, a user can opt in to receiving an Indego Key to be sent in the mail, which allows users to skip procedures involving the station kiosk and unlock the desired bike by tapping the key on its associated dock (Indego, 2019c). Procedures for purchasing a rental pass and unlocking an Indego bike remained unchanged in 2019.

Figure A3: Indego 2020 Mobile Application Interface



Notes: Left image shows a map of Indego stations and the number of bikes available at each. Central image shows a list of available bike stations and the distance to each. Right image shows the in-app menu.