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 services into a major transportation mobile app on ridership in New York City. Specifically, it examines the effect of Lyft's acquisition of Motivate (a bike-share company) and the subsequent inclusion of their bike-sharing services in the Lyft app. Using a rich dataset from the Indego and Citi Bike systems, the study employs difference in differences and triple-difference estimators to compare ridership in New York City and Philadelphia, before and after the integration, among subscriber and non-subscriber groups. The results show a 12 percent overall increase in ridership in New York City, driven entirely by non-subscribers (marginal users), which increased usage by a staggering 79 percent. The findings contribute to the literature on public bicycle usage and technological adoption, highlighting the importance of ease-of-use features in promoting sustainable urban transit and the provision of information. Additionally, the study offers insights into the benefits of integrating different mobility (or other) services into a single platform, supporting the concept of Mobility as a Service (MaaS) in this context. Finally, our results provide valuable information for city planners and policymakers on how to promote cycling, which has the potential to significantly reduce congestion, local air pollution concentrations, and carbon emissions.

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1 Introduction

Pollution and congestion in urban areas are critical environmental and social challenges in many cities around the world. As cities expand and urban populations grow, the resulting strain on infrastructure and the environment becomes increasingly apparent. The prevalence of motor vehicles contributes significantly to these issues, exacerbating air pollution and traffic congestion. This, in turn, impacts public health, the environment, and the overall quality of urban life. As such, various policies have been devised and implemented to deal with the source of these externalities including congestion charges and low emission zones. At the same time, the promotion of cycling as a mode of transportation has also been used as a potential viable solution to mitigate some of these challenges. Bicycles, being non-polluting and requiring less space compared to motor vehicles, offer an eco-friendly alternative that has the potential to significantly reduce congestion, improve local air pollution, and lower the overall carbon footprint of urban transport (Giménez-Nadal et al., 2022; Gössling and Choi, 2015; Hamilton and Wichman, 2015; Chapman, 2007).

Bike-sharing, which provides city dwellers with 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) has become a widespread and pivotal urban mobility strategy that aims to increase the use of cycling with a projected global market of over USD 13.7 billion by 2026 (Rotaris et al., 2022). The literature discussing the factors leading to the adoption of public bicycles is primarily descriptive and the empirical studies on this subject mainly explore what characteristics of a bike-share system are important to users, and their efficacy, and are limited to topics such as how bicycle infrastructure, 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 that may lead to technological adoption, 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 attempt to quantify a causal estimation of how these characteristics, and in particular the use of technology such as apps, can influence ridership.

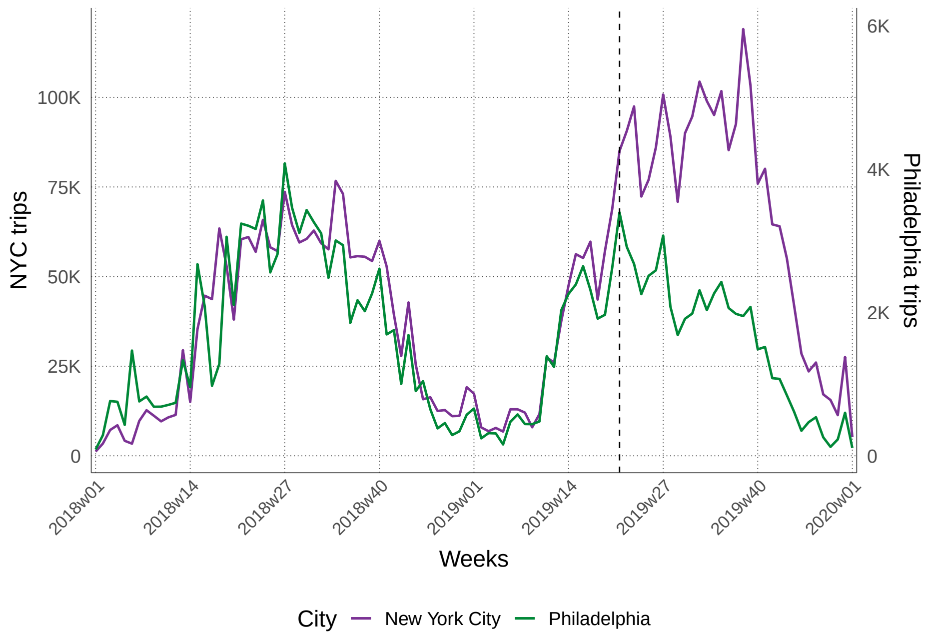
This paper aims to address this gap in knowledge by examining how a technological improvement that simplifies and promotes the use of bike-sharing service via aggregation of transportation service on major transportation mobile apps affects ridership in New Your City (NYC). In particular, Lyft, a ride-hailing company, acquired a public bike-share company, Motivate in 2018, and in May 2019 added its services to their proprietary mobile app (Bradshaw, 2018). Through this launch, Lyft simplified the bicycle rental procedures and pricing structure, as they aggregated the bike-sharing service with their ride-hailing platform (as displayed in Figure 2 and 3) in NYC. This paper estimates the effect of this change on bike-share ridership, leveraging a quasi-experimental variation that stems from three sources. Specifically, our main empirical model uses a triple-difference estimator that compares public bike ridership in NYC with ridership in Philadelphia, before and after the introduction of the bike-sharing information in May 2019, and within subscribers and non-subscribers bike-share rider groups. Hence we not only compare NYC before and after May 2019, but we also use Philadelphia as our control city. We chose Philadelphia because of the following three reasons: (1) it is the closest city to NYC which also operators a large bike-sharing service but in Philadelphia, the ride hail app did not aggregate the bikes; (2) Philadelphia generally is impacted by similar regional macro trends of employment and other economic conditions, and (3), it has a similar weather pattern as NYC.

The empirical analysis, which is based on a rich and publicly available data set consisting of bicycle trips in the Indego (Philadelphia) and Citi Bike (NYC) systems produces the following key results. First, using a simple difference in differences estimator, we find that the treatment, the integration of the public bike-share system in May 2019 to the Lyft app, led to a statistically and economically significant effect on ridership in NYC. In particular, we find that the treatment led to an overall increase of 12% in ridership. Second, we unpacked this overall effect to estimate whether this overall effect comes from subscribers or non-subscribers (marginal users). We find that the overall effect is driven entirely by the latter group, which experiences a 79% increase according to our triple-difference estimation.

Overall, our result provides several important contributions to the literature and policymaking more broadly. First, the results contribute to a growing body of literature regarding the use of public bicycles as a method of urban transportation, and the various factors that lead to adoption when deciding between other common forms of transportation. Importantly, as bike-sharing rapidly grows in popularity across many cities and several continents (Shaheen, Zhang, et al., 2011), city planners will benefit from reliable research demonstrating characteristics of systems that lead to an increased adoption of the bicycle as a practical form of transit.

Second, this paper contributes to literature that explores the diffusion of innovation (Rogers, 2010), and specifically the TAM (Davis, 1989). The results support the notion of users being more likely to adopt a product or service because it is perceived as easy to use (Davis, 1989). Many disciplines of information and technology have been studied through a lens of the TAM (Marangunić and Granić, 2015), however it is increasingly relevant to all sectors of transportation as public planners attempt to encourage adoption of more sustainable versions of transit, and the now common integration of technology in them (Ahn and Park, 2022; Chen and Chao, 2011; Keitel, 2011; Tavilla, 2015; Alliance, 2006; Shaheen, Guzman, et al., 2010; Gao et al., 2019; Jittrapirom et al., 2017). Quantifying a causal increase in ridership of a bike-share program due to improvements of how easy it is to use and due to improvement in information provision can serve as a valuable contribution to the transportation literature, but also a key piece of evidence to public planners for how they might use technology to increase adoption of bike-sharing

Figure 1: 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.

specifically.

Finally, the results of this paper support emerging literature regarding the benefits of integrating new mobility or other services into a single platform, an idea defined as "Mobility as a Service" (MaaS) in the context of transportation, but also referred to as a multi-modal aggregation more broadly (Jittrapirom et al., 2017). Apps like Deliveroo (UK) or Grubhub (US) are examples for somewhat similar aggregators in the context of food delivery and Citymapper and RideScout are other examples of MaaS. This research gives city planners additional motivation to coordinate with private mobility service companies and provide an aggregator app that is fair, efficient, and beneficial to all parties.

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 8 discusses the results and the implications of them, along with the potential limitations of our study. Finally, Section 9 conclude.

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.

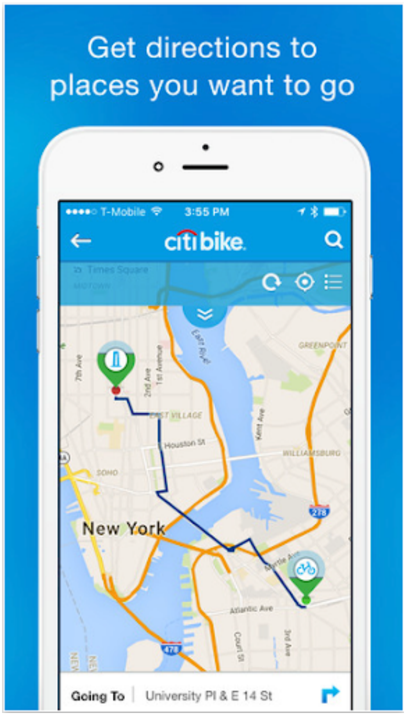
2.1 Citi Bike

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 passes. 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

Figure 2: 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.

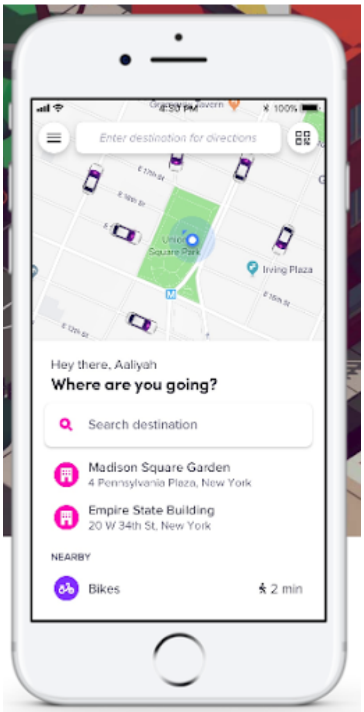
extra \$4 per additional 15 minutes. The annual membership pass cost \$169 and included unlimited 45-minute rides, with rides longer than 45 minutes charged an extra \$2.50 per additional 15 minutes (Citi Bike, 2019d).

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 3. 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 membership (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.

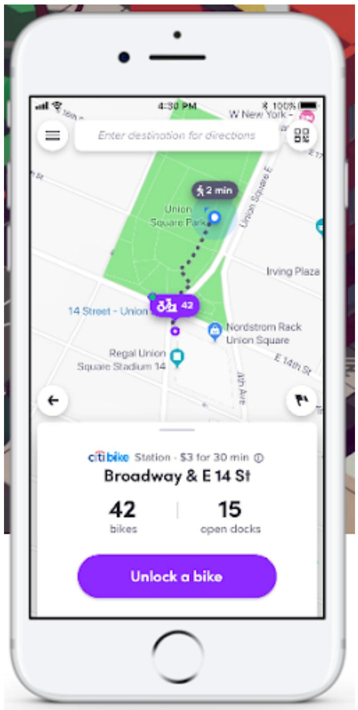
2.2 Indego

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 passes cost \$17/month, with unlimited 60-minute rides, and an extra \$4 for every additional 60 minutes. Annual passes 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). To maintain a strong counterfactual to Citi Bike ridership, we remove data regarding monthly and Indego Flex passes, leaving short-term daily passes and long-term annual memberships. During the window of study, 2019, Indego did not change ownership, but made some small changes to their pricing structure. In April, Indego increased the day pass rate to \$12, and introduced a 15 cent/per minute charge for all pass types for rides with a duration longer than the additional time allotment (Indego,

Figure 3: Lyft mobile application interface post-treatment



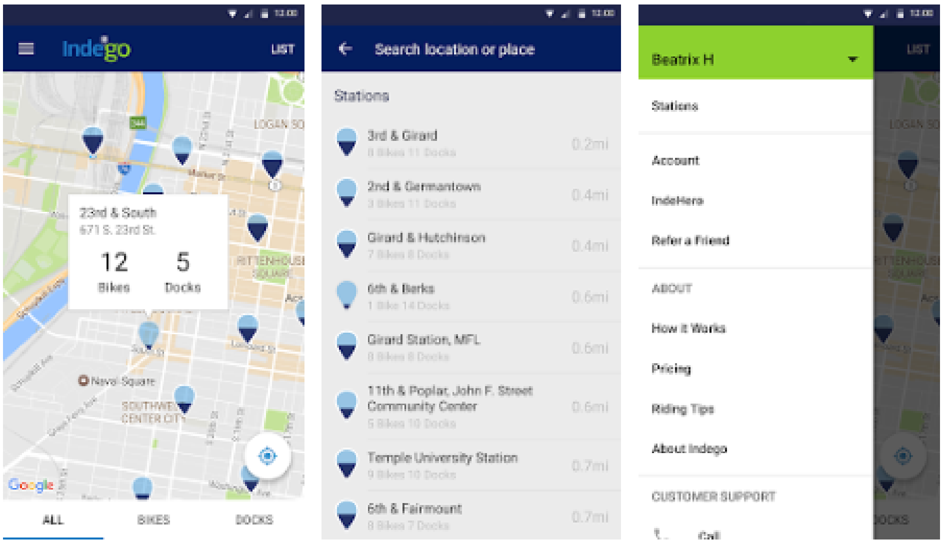
(a) One app, two options: ride-hail or bike-share



(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.

Figure 4: 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.

2019a,b). The bike rental procedure for Indego is detailed in Appendix A.2.

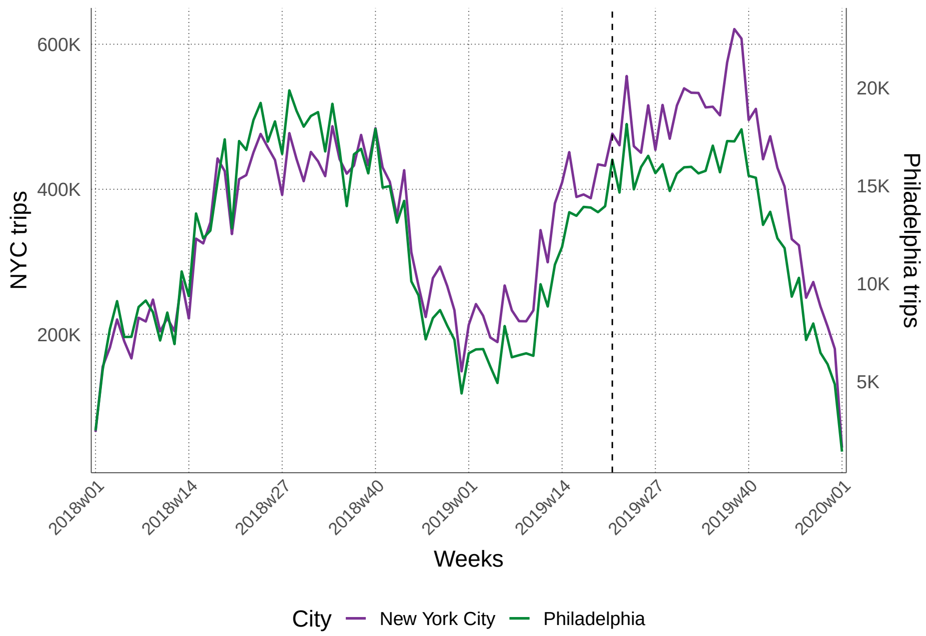
3 Data

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 in 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 pass 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 2019 data is also used for this analysis. The observations contain very similar data 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.

Figure 5: 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, left 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.

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.

4 Methodology

4.1 Event study and parallel trends

Identification through DDD 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 1 lets us inspect the trend among non-subscribers between NYC and Philadelphia. Visually, both lines seem to follow parallel trends prior to treatment, and NYC's non-subscriber membership taking off after the treatment. In addition to the visual inspection of raw data trends, we can statistically test whether the difference between NYC and Philadelphia is significant in the periods prior to and following the treatment. To do so, we specify an event-study model. We regress non-member ridership, $ln(Trips_{jdm})$ on the interaction between pre and post periods k around treatment (period -1 serving as the reference period), with city j and month m fixed effects:

$$ln(Trips_{jdm}) = \alpha + \sum_{k=T_0}^{-2} \beta_k \times Treat_{jm} + \sum_{k=0}^{T_1} \beta_k \times Treat_{jm} + \phi_j + \gamma_m + \varepsilon_{jdm}. \quad (1)$$

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 makes for a fitting control group as it is the closest large city with a bike-share program: thanks to its proximity to NYC, Philadelphia is subject to similar weather but also socio-economic shocks that might affect bike-share 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 each bike-share riders into two groups: subscribers (who purchased annual or monthly passes) and non-subscribers (who purchase individual rides or daily passes). 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 pass, who are therefore much less likely to have the bike-share app installed on their phone and 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:

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

The terms 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 i that also represents the type of riders. Our coefficient of interest is β_7, which capture 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).[1]

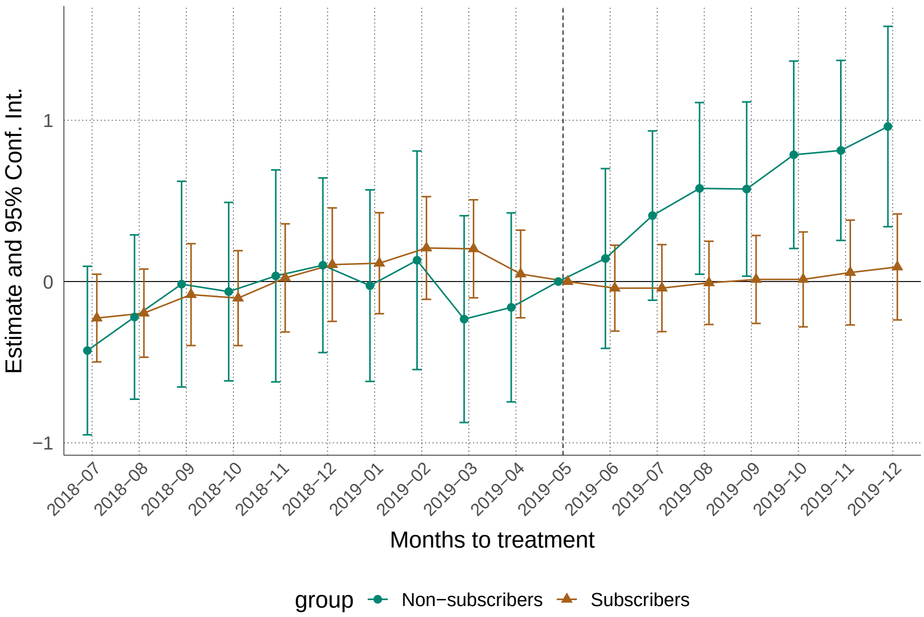
5 Results

5.1 Event study and parallel trends

Figure 1 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.

[1] Our third difference may not entirely remove all potential city-specific time-invariant bias because it is possible that factors such as improved bicycle infrastructure influences subscribers and non-subscribers differently. Section 8.2 discusses this in further detail.

Figure 6: 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 weeks leading to and following treatment (dotted vertical line). The green line (circle symbols) are point estimates for the difference in ridership for non-subscribers, while the orange (triangle symbols) are 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).

Figure 6 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 different before as well as after treatment between NYC and Philadelphia, which indicates that the treatment effect mostly runs through non-subscribers.

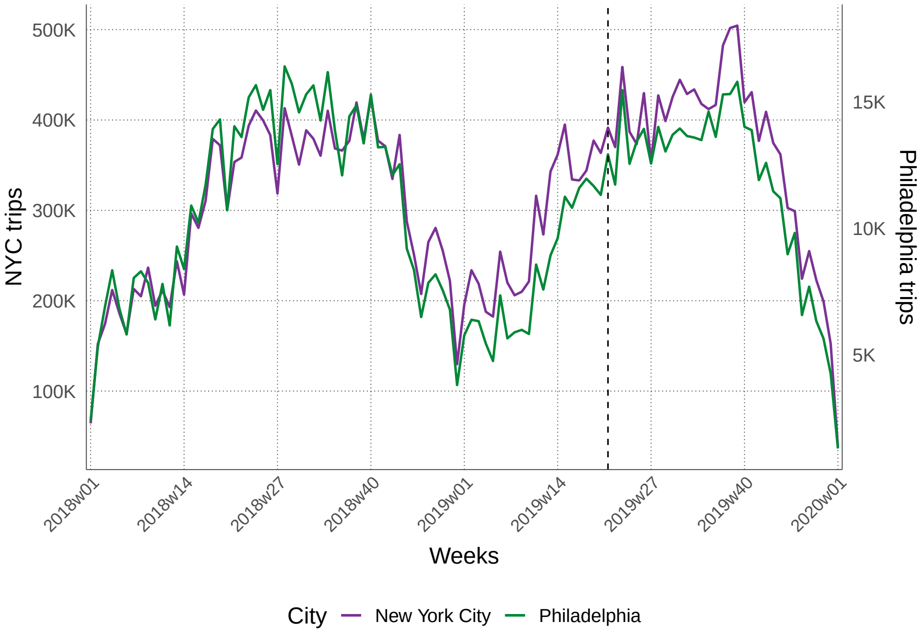
5.2 Difference-in-differences and triple-differences

Table 1: 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**
	(0.0000)	(0.0022)	(0.0000)	(0.0018)
Treated	3.3640***	3.4577***	3.4023***	3.5424***
	(0.0000)	(0.0060)	(0.0000)	(0.0044)
Post-period	-0.0209	-0.0482	-0.1248	-0.1596**
	(0.0179)	(0.0300)	(0.0245)	(0.0073)
Treated × Post-period × Non-subscribers			0.7992***	0.7992***
			(0.0000)	(0.0000)
Treated × Non-subscribers			-0.2851***	-0.2851***
			(0.0000)	(0.0000)
Post-period × Non-subscribers			-0.1047***	-0.1047***
			(0.0000)	(0.0000)
Non-subscribers			-2.2606***	-2.2606***
			(0.0000)	(0.0000)
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: 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*.

Figure 7: 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.

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 12% 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 79% increase in ridership of non-subscribers in NYC, relative to the counterfactual where Citi Bike never received the treatment. A 79% increase in non-subscriber ridership equates to an average of 4,000 more riders daily in NYC using 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 additional 2 metric tons of carbon offset compared to a scenario where the treatment never occurred.

6 Robustness checks

In addition to the event study depicted in Figure 6, we can visually check how the trend in subscriber ridership evolve across cities before around the time of treatment. Figure 7 shows that ridership for the member group stayed fairly constant. In particular, there are

Table 2: 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***
	(0.0000)	(0.0020)	(0.0000)	(0.0016)
Treated	3.4023***	3.4863***	3.1172***	3.3134***
	(0.0000)	(0.0049)	(0.0000)	(0.0039)
Post-period	0.0091	-0.0158	-0.3634	-0.4082*
	(0.0231)	(0.0342)	(0.0721)	(0.0488)
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: 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.

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 column 3 and 4 showed 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.[2] The results confirm those reported in Table 1: the effect of treatment on subscribers is very small around 4%, while the impact on non-subscribers reaches 83%.

7 Heterogeneity analysis

After reporting our headline results in Table 1 that non-subscribers are significantly increasing 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

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

Table 3: Triple differences for non-working and working days

	asinh(trips)			
	Non-working day		Working day	
	(1)	(2)	(3)	(4)
Treated × Post-period × Non-subscribers	0.6360***	0.6360***	0.9707***	0.9707***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Treated × Post-period	0.0122***	-0.0062**	0.0648***	0.0526**
	(0.0000)	(0.0004)	(0.0000)	(0.0021)
Treated × Non-subscribers	-0.4047***	-0.4047***	-0.2318***	-0.2318***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Post-period × Non-subscribers	0.0602***	0.0602***	-0.2086***	-0.2086***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Treated	3.5100***	3.6535***	3.3458***	3.4807***
	(0.0000)	(0.0170)	(0.0000)	(0.0024)
Post-period	-0.0633	-0.1672**	-0.1507	-0.1608*
	(0.0227)	(0.0096)	(0.0361)	(0.0212)
Non-subscribers	-1.5214***	-1.5214***	-2.8123***	-2.8123***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Weather controls		Yes		Yes
Month FE (12)	Yes	Yes	Yes	Yes
Observations	1,808	1,808	4,032	4,032
Adjusted R^2	0.785	0.815	0.899	0.915
Within Adjusted R^2	0.764	0.797	0.893	0.910
RMSE	1.049	0.971	0.768	0.704

Notes: 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: Triple differences for rush-hours and non-rush-hours during working days

	asinh(trips)			
	Outside rush-hour		Rush-hour	
	(1)	(2)	(3)	(4)
Treated × Post-period × Non-subscribers	0.7899***	0.7899***	1.1515***	1.1515***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Treated × Post-period	0.0762***	0.0635**	0.0534***	0.0416**
	(0.0000)	(0.0026)	(0.0000)	(0.0015)
Treated × Non-subscribers	-0.1710***	-0.1710***	-0.2927***	-0.2927***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Post-period × Non-subscribers	-0.1395***	-0.1395***	-0.2778***	-0.2778***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Treated	3.3682***	3.5095***	3.3233***	3.4519***
	(0.0000)	(0.0016)	(0.0000)	(0.0063)
Post-period	-0.1619*	-0.1722**	-0.1395	-0.1495
	(0.0176)	(0.0028)	(0.0548)	(0.0397)
Non-subscribers	-2.4496***	-2.4496***	-3.1749***	-3.1749***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
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: 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.

days. Non-working days are defined as either weekends or holidays.[3] Table 3 shows the result of a triple-difference estimation (see Equation 3) when splitting the sample 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 63% during holidays and weekends, while non-subscriber ridership almost doubled during working days with a coefficient of 0.97.

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. 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.

[3]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).

We explore this effect further by running another triple-difference estimation, this time focusing on working days only by splitting the sample 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 115% during rush-hour after treatment, while the increase outside rush hour is 78%. Taken together, these results clearly suggest that bike-share acts as 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 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 8.[4]

The map indicates that Lyft's integration of bike-share on its ride-hailing app increasing 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.

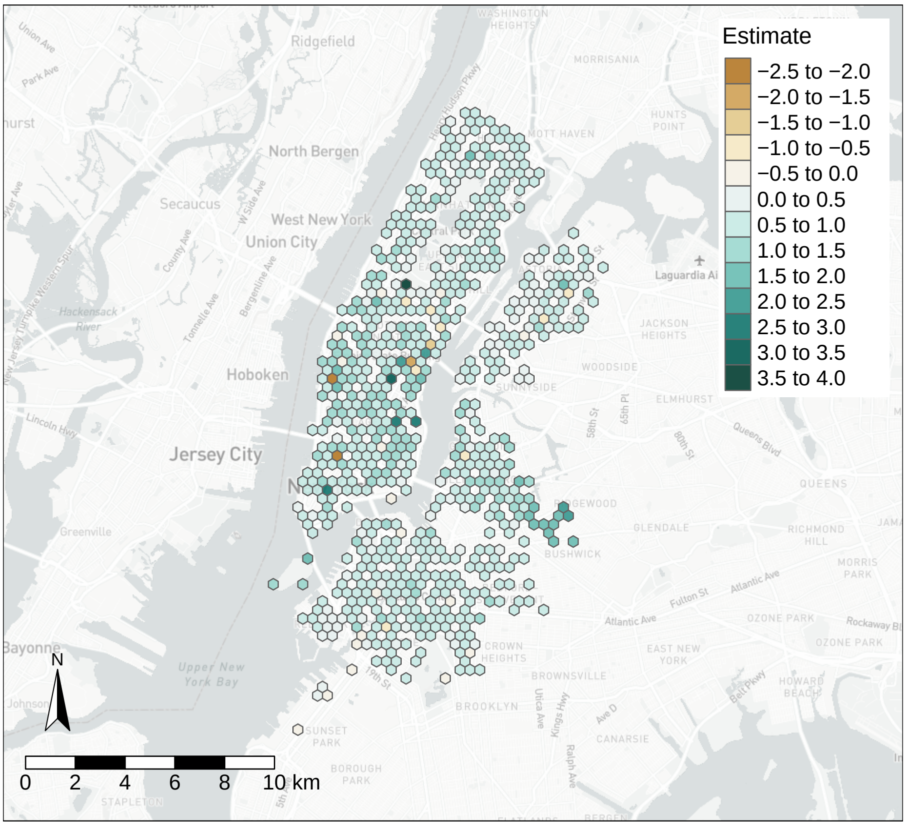
Finally, Figure 9 shows how the distribution of trip duration changed between before and after the treatment in NYC for each user group. According to panel 9a, non-subscribers have increased the duration of their trips after the treatment, while the duration of subscribers' trips has remained largely constant. This may suggest that non-subscribers are switching to bike-share for trips they used to do using ride-hail, the latter being longer trips than what non-subscribers were accustomed to do prior to treatment.

8 Discussion

Our DDD estimator clearly shows a large 77% increase of non-member 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

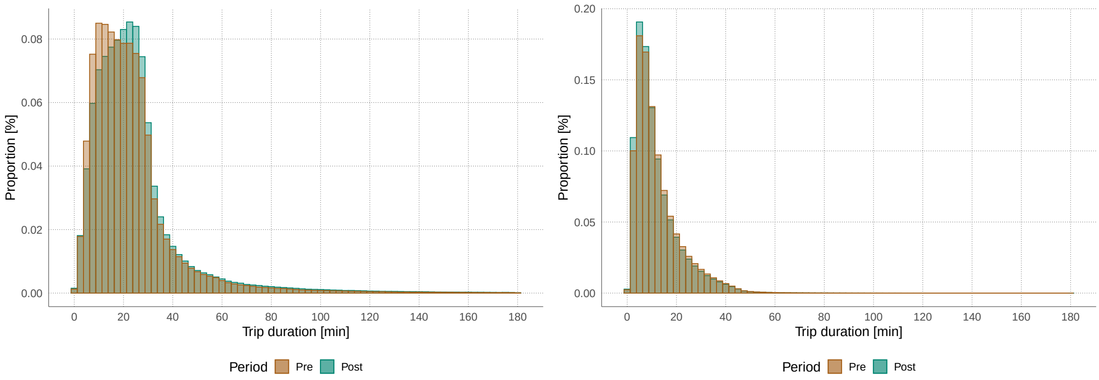
[4]Because some stations opened after the treatment date, we only map cells that reported at least one trip prior to the treatment.

Figure 8: 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 a 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 9: 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.

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.

8.1 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 3. 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 amongst 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.

8.2 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 successfully 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 1 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 members and non-members, 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 were compensated for strategically 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 membership groups differently across time.

Third, it is possible that the changes Lyft made to the Citi Bike system caused non-member users to become members, or vice versa. This is a concern because a time-variant change in the composition of our member and non-member 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 members to become non-members due to the treatment, given annual passes are purchased in full once a year. However, one could argue that the treatment led to a higher rate of trialability amongst non-members, thus encouraging them to incorporate public bikes into their mobility preferences to the point where switching to an annual membership was attractive.

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, the pricing structure of the rental, 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.

9 Conclusion

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 77% increase in non-member ridership, equating to an approximate increase of 12% 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, the research community 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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A Bike rental procedure

A.1 Citi Bike

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
- 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.