Cycling Towards Equity: Assessing the Role of Bike Share Programs in Mitigating Urban Transportation Disruptions and Promoting Inclusive Mobility

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Abstract

This research investigates how bike share systems are utilized under disruptions in public transport and how the impact subsequently converts to increased subscription of the service. Transportation disruptions harm the individual capabilities to continue with commute, which hampers access to essential economic activities and services. Furthermore, the shock affects low-income people much more, imposing higher economic burdens. We examine the efficacy of bike share systems under these dire situations. Through a series of difference-in-differences estimation, we observe several notable findings. First, we find that bike share systems serve low-income neighborhoods when subway operation becomes disrupted. Second, we observe that such an unexpected disruption invokes permanent adoption of latent users in the disadvantaged neighborhoods. Our findings provide relevant managerial and political implications.

Keywords: Bike share systems, transportation disruptions, natural experiment.

1. Introduction

This study investigates the efficacy of bike sharing during massive public transportation disruptions in several aspects. Specifically, we delve into the dynamics of bike share under a significant disruption in public transportation, focusing on the utilization in low-income neighborhoods. Furthermore, we extend our findings to examine how external abnormal events that cause significant inconvenience in daily workday travel behavior can foster the adoption of bike share systems in low-income neighborhoods, leading to sustained utilization in areas that previously incurred relatively low utilization.

Transportation disruptions adversely affect the mobility essential for economic activities and thus cause damage to the urban economy. Based on the available data, the United States incurs costs of up to $389 million annually due to subway delays (Belmonte, 2018). Furthermore, a single occurrence of flood damage to subways may drive the cost much higher. During Hurricane Ida, which brought an unprecedented volume of rainfall to the New York City metro rail systems, the restoration of the system alone incurred costs of up to $100 million (Guse, 2021).

The dire effect of transportation disruptions instigates unequal damages over different members of our society. People of low income are particularly more affected by the regularly occurring disruptions in public transportation such as the reduced services from the pandemic (Lazo & George 2020) and equipment inspections (Kiene 2016). Such inequity in economic loss is more vivid during the larger, disaster-induced subway damages. Low-to-medium-income groups may experience higher economic losses due to flood-induced travel delays (He et al., 2021). The loss due to the impairment of mobility is an addition to the already disproportionate economic damages from urban anomalies.

Although it is crucial in alleviating the incurred loss of economic opportunities, resiliency in transportation is more difficult to achieve for the members whose access to essential economic activity is more desperate. People of low-income and ethnic minorities suffer from transport poverty, which refers to the inability to afford and access diverse transportation options (Lucas et al., 2016).

Closely related, academia has largely left out the empirical examination of how smart mobility systems affect the mitigation behavior of low-income people. The growing body of smart mobility platform literature has considered how smart mobility systems affect public transportation ridership (Babar & Burtch, 2020; Pan & Qiu, 2021), the diverse social consequences of such effects (Greenwood & Wattal,

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2017; Park et al., 2021; Qiu et al, 2022), and more recently, the operations under urban disruptions (Zhang et al, 2023). Here, Zhang et al (2023) propose how ride-sharing platforms support disaster relief of passengers during transportation anomalies but do not consider how the more adversely affected low-income passengers benefit from the platform. Moreover, during hours of heightened demand, the efficiency of ridesharing in low-income neighborhoods become limited by a low baseline supply of riders and surging price (Pandey & Caliskan, 2021).

Such a discrepancy exists for the more affordable version of the smart mobility systems: public bike sharing. Bike share systems have proven to be an effective mode of transportation during transportation disruptions. For example, bike share could act as an alternative to public transportation when they carry a high risk of spreading COVID-19 (Hu et al., 2021). Moreover, the record-breaking level of daily utilization of Citi Bike, the bike share program of New York City (NYC), was achieved when the city's subway system remained largely suspended from the effect of underground flood damages caused by Hurricane Ida (Meyer, 2021). However, the benefits of bike share systems are rarely realized in low-income neighborhoods. Public bike share is disproportionately more popular in the high-income and tourist areas (Reck & Axhausen, 2021). Such a fact has induced system providers to focus on expansions in areas with high income and high tourist volumes (Shaheen et al., 2014). As a result, bike share availability remains limited in the more disadvantaged areas, despite that the preference for the system is comparable to that in high-income areas (McNeil et al., 2018).

Accordingly, while studies and reports communicate the necessity of bike sharing in low-income neighborhoods (McNeil et al., 2018; Dill et al.; 2022), its efficacy during transportation disruptions is subject to ambiguities. Considering the concept of the availability heuristic (Tversky and Kahneman, 1973), people who use bike share when secure transportation is threatened are likely the ones who are already familiar with the system. If such a case is true, enforcing bike share systems in low-income neighborhoods will only have a limited contribution to transportation resiliency. However, from a different perspective, low-income individuals have distinctive economic motivations to utilize bike share during disruptions, as they experience a heavier economic burden when safe commuting becomes difficult. In contrast, high-income commuters tend to prefer comfort over economic issues, and thus often opt for taxis, rideshare, or even telecommuting (Bo et al., 2021). Furthermore, the job positions for low-income commuters require them to be physically present at the workplace (He & Hu, 2015). Therefore, pressure to mitigate any unexpected inconvenience in essential travel is felt heavier for low-income passengers, while having few viable alternatives (Kontou et al., 2017). By examining the efficiency of bike sharing under transportation disruptions and investigating the heterogeneity caused by the areal income level, we attempt to provide novel implications for expanding bike share services in low-income neighborhoods.

In addition, we also examine the financial incentive to site bike share stations in low-income neighborhoods. Often the equity expansion efforts are faced with the pressure that the system must be profitable, at least to a degree that it can survive on its own (Gallucci, 2021). Paired with education programs, promotion events, external fundings, and discounted memberships, the bike share service providers are seeking to boost system acceptance among low-income neighborhoods (McNeil et al., 2019), but there is scarce investigation of what drives sustained adoption of bike sharing in low-income neighborhoods. Accordingly, we examine whether the heightened demand for bike share induced by an external shock that increases the short-term inconvenience in transportation can act as a catalyst for system awareness and consequently lead to permanent adoption of the system.

In summary, we attempt to provide new insights into how bike-share systems become utilized during a transportation crisis and examine whether short-term demand shocks lead to permanent adoptions. Specifically, we attempt to draw clear evidence of whether bike share disproportionately serves high-income travelers or equitably serves low-income travelers. In addition to investigating the change in utilization of bike share, we imply whether bike share companies can seek an increase in membership by communicating the adaptability of these systems in the areas where public transportation is less reliable. Accordingly, we examine the following research question:

How does bike share differ in its contribution to transportation disruption management in neighborhoods of different economic statuses?

To derive an answer to this question, we focus on a distinctive setting: the abrupt shutdown of the subway system in New York City (NYC) caused by Hurricane Ida of 2021. After Ida dissipated, but the subway operations remained largely disrupted, the officials of Citi Bike, NYC's public bike-sharing brand, announced that daily ridership has recorded an all-time high since its launch (Meyer, 2021). Accordingly, the objective of this study is to examine the impact of flood damage on subways on the utilization of bike sharing.

2. Related Works

2.1 Effects of Smart Mobility Services

With our reliance on shared mobility growing, society expects that these shared mobilities, such as ridesharing, car sharing, bike sharing, and e-scooter sharing, will take a pivotal role in providing access to essential economic activity. Accordingly, there has been growing academic interest regarding its effect on the existing urban transportation landscape. Several studies have investigated whether the entry of shared mobilities complements or replaces public transportation demand (Hall et al., 2018; Babar & Burtch, 2020; Pan & Qiu, 2021). A different group of studies investigates how the significant shift in transportation demand affects diverse social issues. Greenwood and Wattal (2017) discovered that ridesharing can reduce alcohol-related vehicle fatalities. Park et al., (2021) suggest evidence that ridesharing reduces the number of sexual assault incidents. Li et al., (2022) provide evidence that ridesharing alleviates traffic congestion. In a more recent investigation into how ridesharing performs under unexpected urban anomalies, Zhang et al., (2023) propose that ridesharing is much more efficient in supporting disaster relief of passengers compared to the traditional taxi services.

However, studies suggest that the effect of ridesharing is subject to spatiotemporal conditions. For instance, although ridesharing is efficient in supporting the evacuation of passengers from anomalous events (Zhang et al., 2023), it also becomes the most expensive at times of heightened demand due to the algorithmic failures of the dynamic pricing scheme (Zhang et al., 2023). Accordingly, the significant effect of ridesharing entry on the reduction of alcohol-related vehicle fatalities becomes minimal when rising demand instigates high prices (Greenwood and Wattal, 2017).

2.2 Disruptions in Urban Transit

The fact that ridesharing efficacy can vary over local characteristics has high relevance to the issue of social justice and equality. A significant body of literature discusses what inequality in mobility means for the socially disadvantaged. The low-income population suffers from chronic insecurities in transport (Murphy et al., 2022). The poor baseline security in transport exerts disproportionate effects on low-income neighborhoods (Rubin et al., 2021). In a comprehensive report, Rubin et al. (2021) analyzes the lost economic opportunities from transport delays and find that the loss is felt much heavier by low-income commuters. He et al. (2021) report how flood-induced suspension of commuting rails exercises a disproportionate effect on job accessibility, which can even cause job loss. What further aggravates the current situation is that scholars expect climate change to increase the frequency of transport disruptions caused by extreme weather events such as floods (Sun et al., 2022).

Relatedly, transportation studies have made significant contributions regarding the behavioral change of commuters when the security of commute becomes enfeebled. Transport disruptions, including delays and suspensions of public transport, induce commuters to conduct modal shifts to alternative transport (Kontou et al., 2017). While reports state that disruptions in services are chronic for most passengers (Stringer, 2017), many studies find that low-income users lack the option to conduct modal change, which the reason includes affordability (Miller & Savage, 2017; Zhu et al., 2017).

However, shared bicycles incur significantly low prices while being as fast as ride-hailing services in urban areas (Faghih-Imani et al., 2017). For instance, in NYC, a 30-minute ride via Uber or Lyft will cost the passenger around $27.15 (Dolmetsch & Davalos, 2022), while the same length of a trip will cost only $4 for Citi Bike, the bike share operator of NYC. However, although several studies suggest the potential of bike sharing functioning as an adequate low-cost alternative to ride-hailing services amid disruptions (Green et al., 2012; Zhu et al., 2017), empirical examination of the difference in mitigation behavior between socioeconomic groups is yet to be conducted (Yang et al., 2022). Accordingly, this study examines the efficacy of bike sharing in alleviating transportation concerns in disadvantaged areas by investigating the difference in the change in utilization among neighborhoods of different economic statuses amid a transportation disruption.

3. Data

We have collected publicly available datasets to leverage our natural experiment context. Primarily, we utilize the open datasets of bicycle trip information provided by Citi Bike of NYC to estimate the impact of subway flood damages on bike share utilization. Additionally, we leverage datasets from major bike share operators in different regions of the United States to create a counterfactual Citi Bike system that was not affected by the subway flood damage.

Specifically, we gather ridership data from Indego Bikes in Philadelphia, Blue Bikes in Boston, Bay Wheels in San Francisco, Divvy Bikes in Chicago, and Capital Bikeshare in Washington, D.C.

The collected trip data includes information about the time and coordinates of each pickup instance. Subsequently, we aggregate the pickup times to the daily level and the pickup coordinates to the census tract level, which is the smallest geographic unit for gathering socioeconomic statistics. These datasets are then aggregated to construct a panel dataset that summarizes the total number of bicycle pickups on each date.

Second, we collect socioeconomic statistics of each pickup location, or the census tract. To address our research question, we attempt to capture the effect of flood damage on subway lines on the daily bike share demand. Therefore, in the efforts to factor in area-specific socioeconomic traits that potentially influence bike share demand, we obtain datasets containing detailed information on areal socioeconomic characteristics from the American Community Survey (ACS) conducted by the U.S. Census Bureau. A census tract area is approximately half the size of a zip-code area, allowing us to control for observed heterogeneities of the neighborhoods with detail. In consequence, our identification of the low- and high-income neighborhoods is determined by the median household income level of each census tract area. Specifically, we identify the areas with income level lower than median as the low-income areas. Additionally, we leverage information regarding the percentage of commuters commuting by public transportation, percent of commuters commuting by car, the number of people employed, the number of people receiving SNAP benefits, and the average time spent commuting. With the unique identification codes given to each census tract area, we could match the neighborhood statistics to the bike share pickup locations indicated in the panel data.

4. Methodology

4.1 Difference-in-Differences Framework

We construct a triple-differences (TD) model to draw causal inference between the effect of subway flood damage of NYC during 2021 and the subsequent utilization in ridership. Viewing the flooding and the subsequent shutdown of subway systems as a possible external shock to the demand of bike share allows us to exploit a quasi-experimental setting.

The specification of the model is given as follows:

$$\log(num\_bike_{it}) = \alpha_i + \beta_1(NYC_i \times Post_t) + \beta_2(NYC_i \times Post_t \times low\_income_i) + \beta_3(Post_t \times low\_income_i) + Z_{it}\gamma + \theta_t + \varepsilon_{it}.$$

Here, num_bike_{it} is the dependent variable representing the total number of rides occurring in census area i during time period t. $NYC_i \times Post_t$ indicates whether the flood has affected neighborhood area i at time period t. Our main interaction variable of interest is $NYC_i \times Post_t \times low\_income_i$, where β_2 indicates the effect of subway flood damage on the bike share utilization in low-income neighborhoods. Subsequently, α_i and θ_t represents the tract-fixed effects and time-fixed effects respectively. Finally, Z_{it} and ε_{it} represents the vector of control variables and errors, respectively. As for the control variables, we include the variation in average wind speeds in miles per hour, average temperature, and average precipitation in millimeters. These weather-related factors are known to affect bike share utilization (Gebhart & Noland, 2014). The description and summary statistics of the control variables used are provided in Table 1.

Table 1. Summary statistics

Variables	Description	Mean	S.D.	Min	Max
Num_bikes	Number of daily bike share trips	53	82.41	0	762
Temp	Temperature in Fahrenheit	75.95	7.036	60.00	87.00
Wind	Wind speed in mph	15.73	5.537	3.00	29.00
Precipmm	Precipitation in millimeters	2.689	8.825	0	47.750

Notes: Because the standard deviation of Precipmm and num_bikes are much larger than the mean, we use log-transformed values throughout the analysis.

4.2 Propensity Score Matching

We use the propensity score matching technique with the set of observed time-invariant covariates in the dataset. NYC deviates from other cities in its peculiarity in terms of the public transit landscape. In addition, there exists significant areal variance between neighborhoods of different income. Therefore, we perform propensity score matching between (1) the two income groups and (2) neighborhoods in NYC and other cities. When matching the income groups, we consider the percent of residents commuting by public transit and the percent commuting by personal vehicle, to control for the degree to which these neighborhoods were affected by subway flood damage. The balance of covariates after matching is presented in Table 2. Specifically, we match the areas based on median household income (to control for the difference in wealth between areas of NYC and the counterfactuals), number of people employed (to control for the difference in commuting demand), the number of people that are receiving SNAP benefits (to control for the wealth disparity), and mean travel time to work (to control for the variation in commuting difficulties).

Table 2. Matching income groups

Commuting Profiles Before Matching			
	Low-income	High-income	Difference
% Commuting by Public Transit	39.485	32.307	0.334
% Commuting by Personal Vehicle	36.422	36.513	-0.004
Commuting Profiles After Matching			
	Low-income	High-income	Difference
% Commuting by Public Transit	33.704	34.380	-0.037
% Commuting by Personal Vehicle	40.578	37.801	0.127

Table 3. Balance of covariates

Balance of Covariates After Matching: Low Income			
	Treated	Control	Difference
Median household income	50491.133	49152.659	0.072
Number employed	2159.857	2101.655	0.043
Population receiving SNAP	427.452	424.310	0.006
Mean travel time to work	38.267	38.676	-0.067
Balance Covariates After Matching: High Income			
	Treated	Control	Difference
Median household income	127784.500	130290.111	-0.071
Number employed	2681.632	2883.164	-0.126
Population receiving SNAP	84.194	91.038	-0.058
Mean travel time to work	32.732	32.355	0.060

The balance of covariates after matching the treated areas and not-treated areas is displayed in Table 3. After matching, we obtained a panel data with 8,008 observations, with 1144 unique census tract areas and 7 workdays around the treatment period. Specifically, we include four workdays before and three workdays after September 1, the day that NYC reported significant flood damages throughout the city's subway lines. The obtained data is a balanced panel.

5. Results

5.1 Utilization of Bike Share

Initially, in Column (1) of Table 4, we present the causal effect of subway flood damages on the full sample, namely, the general effect unconditional on the areal income level. The coefficient for the interaction term $NYC_i \times Post_t$ is positive and significant, indicating that there was a significant increase in the bike share utilization from the effect of subway suspensions.

Interestingly, in the subsequent column, we see that the impact of flood on the bike share utilization hinges on the level of income in the affected area. Column (2) of Table 4 shows the effect of flood on the number of bike share rides in low-income neighborhoods. We discover that the coefficient for $NYC_i \times Post_t \times low\_income_i$ is much larger than the simple two-way interaction in Column (1). The positive and significant coefficient of 0.135 indicates that in the low-income neighborhoods, the subway flooding has caused an increase of 13.5% in the bike share ridership in the low-income neighborhoods of NYC.

Table 4. Main results

	(1)	(2)
Variables	***num_bike$_{it}$***	
NYC× Post_Ida	0.062** (0.028)	0.000 (0.039)
NYC×Post_Ida× low_income	-	0.135** (0.050)
Temp	-0.002 (0.001)	0.001 (0.001)
Wind	-0.000 (0.001)	-0.003* (0.001)
Precipmm	-0.064*** (0.006)	-0.065*** (0.006)
Post_Ida×low_income	-	-0.103*** (0.028)
Area Fixed Effects	Yes	Yes
Time Fixed Effects	Yes	Yes
R^2	0.019	0.035
Observations	8,008	8,008

*Notes: *p < 0.1, **p<0.05, ***p<0.01*

However, the impact of the flood appears to be minimal in higher-income neighborhoods. When accounting for the effect heterogeneity in low-income neighborhoods in Column (2), the coefficient for the two-way interaction, $NYC_i \times Post_t$, becomes insignificant, suggesting a negligible increase in bike share usage in high-income neighborhoods.

Although our model rules out the possibility of serial correlation by clustering the standard errors at the tract level and includes fixed effects to avoid unobserved unit- or time-specific factors affecting our results, DID estimation is subject to potential bias from unobserved time-varying confounders. The common practice to statistically examine whether the estimated difference is a result of unobserved time-varying confounders is to check for parallel trends in pre-treatment outcomes. Therefore, to allow credibility of the results, we estimate a relative time model for the confirmation of insignificant pre-treatment differences between the treatment and control groups. The result of the relative time model for the TD model, examining the treatment heterogeneity in low-income neighborhoods at each time period, is presented in Table 5. The estimation of the relative time model suggests that the outcome satisfies the parallel trends assumption.

Table 5. Validation of parallel trends

Time to treatment	num_bike_{it}
T-3	0.106 (0.065)
T-2	0.044 (0.072)
T-1	0.020 (0.062)
T-0	Baseline
T+1	0.117 * (0.061)
T+2	0.121*** (0.053)
T+3	0.055** (0.057)
Control Variables	Yes
Area Fixed Effects	Yes
Time Fixed Effects	Yes
R^2	0.037
Observations	3,248

*Notes: *p < 0.1, **p<0.05, ***p<0.01*

5.2 Extension of Findings

So far, we have demonstrated that the flood damage of the metro system of NYC incurred significant increase in the number of bike share rides, which helped Citi Bike to record highest-ever number of rides (Meyer, 2021). We could also see that the increase in utilization occurs by a larger relative margin in low-income neighborhoods. We consider this a direct contribution to transport resilience of the transport poor. To elaborate, bike share allows low-income communities to conduct modal shift to bikeshare from public transportation under transportation disruptions.

Nonetheless, the observed effectiveness of bike share would lack substantive significance if corresponding enhancements and refinements to the current bike share system are not implemented. Despite a pronounced preference for bike share within low-income neighborhoods and the willingness of both bike share operators and city officials to invest in these areas (McNeil et al., 2018), certain challenges persist. While the most significant barrier for low-income individuals to utilize bike share is the availability and network density itself (Dill et al., 2022), there remains a high level of uncertainty regarding the sustainability of bike share systems in low-income neighborhoods.

In our main analysis, we illustrated that a comparable transportation disruption can result in a notably higher shift towards bike share usage within low-income neighborhoods. In these communities, concerns about transportation security are elevated, and even minor irregularities in public transportation can lead to significant transit inconveniences. Consequently, we posit that unforeseen anomalies, such as subway suspensions, can serve as a catalyst that highlights the utility of bike share as a reliable alternative. In addition, there is strong evidence that short-term unexpected shocks induce individuals to permanently adopt previously unused technologies (Dupas et al., 2014). Closely related, we attempt to extend the notion to the case of smart mobilities.

Subsequently, we turn our attention to examining whether the significant short-term demand shock for bike sharing in low-income neighborhoods could have led to permanent adoption or an increase in subscriptions. To estimate the change in subscriptions, we have made several adjustments to our estimation strategy. First, we now analyze the change in the weekly level of ridership, including 7 weeks before and 7 weeks after the flood event. To ensure our results are not confounded by unobservable environmental changes associated with the transition to the winter season, we do not extend the analysis beyond these time periods.

Second, we differentiate between non-member and membership rides from the weekly totals using the collected bike share trip data. The dataset provides information on whether the trip was paid for using a one-time use ticket or through a membership status. Leveraging this dataset, we aim to determine if there is a significant change in the number of membership trips.

Third, to investigate the effect of short-term contingent adoption of bike share on long-term subscriptions, we estimate two relative time models. Specifically, we formulate one model that estimates the unique change in non-member bike share trips to capture the early change in the number of casual trips over time. Another model estimates the change in membership trips in low-income neighborhoods over time. It's important to note that we extend upon the TD model, meaning that each relative time model accounts for the change in ridership unique to the low-income neighborhoods.

Lastly, we check for potential confounding effects of cycling events that may have boosted utilization in the post-treatment weeks. We do so by examining the history of cycling events held by the NYC Department of Transportation. Our investigation confirms that no such events were held during the workdays, which constitutes our sample period.

The extended TD model, or the relative time model, can be expressed as:

$$
\begin{aligned}
\log(num\_bike_{it}) = \alpha_i &+ \sum_{k=1}^{K} \beta_k I(t = t_0 + k) \times NYC_i \\
&\times low\_income_i \\
&+ \sum_{j=1}^{J} \beta_j I(t = t_0 - j) \times NYC_i \\
&\times low\_income_i + \gamma Z_{it} + \theta_t + \varepsilon_{it}.
\end{aligned}
$$

Here, $I(t = t_0 + k)$ is a binary variable that takes the value of 1 if the time period of the observation was exactly k weeks after the subway flood damage. Similarly, $I(t = t_0 - j)$ takes the value of 1 if the time period of the observation was exactly j weeks before the treatment. Note that *k* and *j* both range from 1 to 7 as we consider 7 pre- and post-time periods in this model. Also, this model automatically checks for the parallel trend assumption by estimating $\sum_{j=1}^{J} \beta_j I(t = t_0 - j)$, the pre-treatment differences at each week.

Column (1) of Table 6 provides an overview of the results related to the estimation of the change in the number of casual trips. Initially, we detect a noteworthy and positive treatment effect one week after the flood. This implies that the subway flood damages have drawn in low-income users who were not previously regular users of the system. Additionally, we observe sporadic increases in bike share trips that were not evident before the subway suspension incident. To summarize, we reaffirm that the sudden subway damages have had a substantial impact on bike share demand in low-income neighborhoods.

Column (2) of Table 6 presents the estimation results concerning the change in the number of membership rides. Initially, we do not observe a significant change in membership trips during the first four weeks after the treatment. We find this result intuitive, as it is reasonable to assume that the short-term surge in demand among low-income passengers would not immediately lead them to decide to become regular members, incurring an annual cost of $205.

Table 6. Long-term effects

	(1)	**(2)**
Time to treatment	***casual_bike$_{it}$***	***member_bike$_{it}$***
T-6	-0.088 (0.080)	-0.101 (0.073)
T-5	-0.020 (0.072)	0.002 (0.071)
T-4	0.075 (0.072)	0.043 (0.069)
T-3	0.018 (0.072)	0.084 (0.069)
T-2	0.034 (0.064)	0.071 (0.068)
T-1	-0.046 (0.067)	0.005 (0.059)
T-0	Baseline	
T+1	0.209*** (0.063)	0.021 (0.060
T+2	0.071 (0.063)	0.036 (0.058)
T+3	0.207*** (0.067)	0.017 (0.067)
T+4	0.149** (0.070)	0.021 (0.066)
T+5	0.056 (0.078)	0.153** (0.071)
T+6	0.176** (0.083)	0.186*** (0.071)
T+7	0.078 (0.081)	0.160** (0.071)
Control Variables	Yes	Yes
Area Fixed Effects	Yes	Yes
Time Fixed Effects	Yes	Yes
R^2	0.015	0.013
Observations	11,448	11,448

*Notes: *p < 0.1, **p<0.05, ***p<0.01*

However, a statistically significant increase in membership trips becomes evident starting from the fifth week into the post-treatment period. Considering the observed early increase in the number of casual trips, it is plausible to infer that latent users have undergone a "trial period," likely initiated by the sudden disruption of subway lines in NYC.

6. Conclusion

We arrive at several highly relevant findings for bike share system operators and governors. First, through a DID analysis, we confirm that the flash flooding of NYC in 2021 has caused the number of bike share rides to increase in the lower-income neighborhoods while not having much effect on the wealthier. This suggests that in times of abruptly imposed economic hardship, bike share use in low-income neighborhoods can increase. This finding is novel in that it suggests that bike share use may increase not only during planned disruption in public transit (Cheng et al., 2021), but also during abrupt disruption caused by an external shock. The results also indicate that during unforeseen crises, the demand for bike share not only stays relatively consistent for areas of low income (Hu et al., 2021) but also may increase substantially.

Furthermore, we have observed that sudden transportation disruptions can prompt low-income individuals to enter a trial phase, potentially leading to the permanent adoption of the bike share system. This represents a novel discovery that offers valuable insights into how bike share system operators can approach their equity expansion efforts. Often, initiatives aimed at enhancing equity within the bike share network face the challenging requirement of achieving profitability, even if only to a modest extent. Our analysis indicates that while the baseline demand may be low due to financial constraints and limited bike share availability, a significant number of latent users have yet to recognize the system's utility.

Moreover, considering the frequent and unexpected inconveniences in public transportation that affect low-income areas disproportionately, we posit that bike share has the potential to capitalize on these anomalies as opportunities to attract more users while establishing itself as a reliable mode of transportation. This dual role, as a solution to short-term transportation challenges and a sustainable mode of transit, underscores the significance of continued investment and promotion of bike share systems within low-income neighborhoods. It aligns with the broader goal of fostering equity and resilience in urban transportation networks.

6.1 Discussions

This study has several theoretical and practical implications. Theoretically, this study contributes to the literature on the societal impacts of smart mobility systems. We shed light on the previously undiscovered dynamics of the utilization of bike share systems under transportation disruptions and suggest how the bike share system may have alleviated the abruptly imposed economic cost. Practically, our findings contribute as a rationale to fund the equity programs of bike share systems in previously underserved venues. Future research could extend our findings and scrutinize whether these substitutional adoptions of bike share systems can lead to permanent adoptions.

We acknowledge several limitations of our study that provide future research opportunities. First, our study considers a unique setting: large-scale disruption of subway lines in NYC caused by a natural disaster. Leveraging such a massive event allows us to leverage a large sample size and imply the efficacy of bike sharing during disaster-induced damage to subway lines. However, it also limits the generalizability to smaller-scale disruptions, such as minor delays. Therefore, future research should explore the applicability of our insights to a wider range of transportation disruptions.

Second, the sample we use has limitations in representing the currently underserved low-income communities. Because Citi Bike of NYC does not provide free-floating pickup/drop-off service, we relied on making an analogy among neighborhoods that have subway lines in proximity and bike share stations applied. Followingly, there is a possibility that the currently underserved low-income neighborhoods, which are even more disadvantaged compared to the low-income areas in our sample, could be significantly affected by other factors (e.g., crime rate, unemployment rate, and road infrastructure) to a degree that the same phenomenon cannot exist. Therefore, we call for studies to conduct an exploration of factors that hampers the conversion to bike share in low-income neighborhoods when commuting becomes difficult.

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