



The Role of Bike Sharing in Promoting Transport Resilience

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Abstract

A resilient transport network, which is significant for urban sustainability and security, is characterized by its ability to recover from disruptions subject to natural and man-made disasters. Bike sharing could act as a viable alternative in the case of public transit disruptions given its flexibility and various social, environmental, and economic benefits. This study aims to estimate quantitatively the potential of bike sharing to promote transport resilience, by using autoregressive negative binomial time series model to investigate the effects of public transit closures on bike sharing demand in Washington, D.C. area during 2015–2017. We find that (1) bike sharing can act as a supplementary mode to enhance urban transport resilience in the case of complete transit closure; (2) the proximity of bike sharing docks to metro stations has a powerful effect on propensity to use a bike sharing program; and (3) extreme weather is one of major barriers to bicycling. Planners can enhance resilience of urban transport networks by fully considering the capacity and usage of bike sharing docks, as well as the coherence of metro stations and bike sharing docks, in distributing and rebalancing activities.

Keywords Transit disruption · Bike sharing · Transport resilience · Urban sustainability

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1 Introduction

The transport system, as one specific crucial infrastructure system, is fundamental to the functioning of the society in developed as well as developing countries, acting as a lifeline for economic value creation and for repairing other infrastructure systems (Mattsson and Jenelius 2015). Transport resilience is defined as the ability of the transport network to withstand the impact of extreme weather, to operate in the face of such events and to recover promptly from its effects (Cox et al. 2011; Bešinović 2020; Department for Transport 2014). Transport resilience contributes more broadly to a society's economic resilience, which can be understood as increasing the adaptative capacities of societies by reducing nodal vulnerabilities (Darayi et al. 2019). Increasing the resilience of transport system has become a priority for policymakers, as one pathway to imagining a sustainable and secure society and to overcoming the vulnerability of transport system due to various natural and man-made sources of disruption. A characteristic of a resilient and robust transport network is its ability to recover from disruptions, which can be enhanced by introducing redundancies. However, the associated investment in multimodal interchanges can be quite expensive. Sustainable and feasible strategies call for effective management of existing infrastructure which relies on thorough understanding of the underlying complexity of the network systems when disruptions occur (Chow et al. 2015).

In recent years, public transit disruption has become a common occurrence, both due to external factors, such as natural disasters, strikes and emergencies (Lin et al. 2016), and internal factors, including system failure and infrastructure maintenance. In the case of transit disruptions, affected transit users may react by adjusting their routes, departure times, travel modes, and destinations or by canceling trips (Zhu et al. 2017). These adjustments are important to explore because they may alter default travel modes of unaffected travelers and disrupt equilibrium of current public transit systems. However, most research on public transit service closure is based on strikes and accidents which are unpredictable and only have a short-term impact. Research on prolonged and planned transit service disruption is limited; these will force travelers to use alternative modes and provide a glimpse at new travel patterns that could be adopted.

Bike sharing is a new form of transport mode and is becoming increasingly popular in cities around the world (Zhang and Mi 2018). With flexibility and various social, environmental, and economic benefits, bike sharing could act as a viable alternative in the case of public transit disruption. It can also be considered as a useful strategy to accelerate needed changes in personal transportation choices to foster structural change towards sustainable societies (Mi and Coffman 2019). First of all, the capacity and service scope of bike sharing docks continue to expand, making it possible to easily access a bike or bike parking. Next, bike sharing is cost-efficient compared to private automobiles, especially for short distance commutes. Thirdly, bike sharing has positive environmental effectiveness and health effectiveness, including reducing congestion, improving air quality by replacing private vehicles in short trips and improving the health of residents (Institute for Transportation and Development Policy 2018).

This main purpose of this study is to explore the role of bike sharing during planned and long-term disruption of transit service (hereafter referred to as surges, detailed information of each surge is shown in the supplementary information). This study enriches extant research by using transit disruption as an experimental way to identify the impact of maintenance type, influential radius and biking distance on bike sharing demand. Our

method takes trip-level activities (number of trips between docks within an influential radius of affected metro stations) into consideration rather than station-level activities (total number of trips originating from a dock) to better understand the impact of surges (Hajdu et al. 2019). The results provide clear evidence that bike sharing is used as an alternative transit mode during transit disruptions periods. This is of importance to planners as it indicates that a radical shift in transport policy promoting environmentally friendly travel patterns is possible, which provides guidance for transit agencies to take appropriate actions to increase resilience and robustness in public transit system.

2 Literature Review

Planned metro disruptions are not unusual as a result of increasing maintenance needs for aging infrastructure, system failures, and man-made or natural disasters (Marsden and Docherty 2013). It is a widely used practice to bridge affected lines using parallel replacement buses (Zhu et al. 2017), which is of limited utility considering its relatively low capacity compared to metro lines and the frequent occurrence of congestion in surface traffic networks. Transit agency thus are incentivized to increase investment in multimodal interchanges.

Unlike day-long strikes or emergencies, long-term metro closure due to maintenance usually results in travelers being informed well in advance. Well informed travelers can adjust their travel modes to respond. These adjustments can be seen as adaptations of travelers to abrupt changes, which also provide evidence that a more significant and rapid change in travel policy and travel patterns to achieve eco-friendly mobility are possible (Younes et al. 2019). From this perspective, long-term transit disruptions are in fact an opportunity through which to construct through experimentation a different approach to transport policy that might enable environmentally friendly changes, rather than simply to frustrate significant numbers of travelers (Marsden and Docherty 2013).

Over the last two decades, the bike sharing system has expanded substantially around the world. There are three reasons that account for the rapid development of bike sharing programs in metropolitan areas worldwide. Firstly, the government is increasingly responsive to the negative externalities of motor vehicle use, including exhaust pollution and traffic congestion (Fishman 2016). Secondly, as a key component of future smart cities, bike sharing services offer more flexibility than standard public transportation, while also providing considerable environmental benefits and health gains (Shaheen et al. 2010; Fishman et al. 2014; Zhang and Mi 2018). Lastly, bike sharing can benefit multimodal interchanges by acting as an efficient solution for first- and last-mile issue, which is caused by the built and social environment (Tilahun et al. 2016). Public transport service availability in the first/last leg of the trip generally are constrained in cities worldwide (Fan et al. 2019). Bike sharing is considered as a viable alternative in the case of transit disruptions, especially planned system closures (Younes et al. 2019), due to its easy access and convenient parking. An integrated approach to public transport, with bike-sharing schemes supplementing standard bus and light rail systems, can improve transit times and encourage the shift towards a more sustainable urban mobility (Brons et al. 2009; Buehler and Pucher 2012).

Despite the potential of bike sharing as an alternative travel mode in the case of planned transit disruption, most research on public transit closure has paid attention to

motorized mode shift during and after each period of disruption using stated and revealed preference surveys (Hampshire et al. 2017; Lin 2016; Zhu et al. 2017; Yang 2018) without considering bike-sharing as a choice.

To date, there are only limited studies examining the impact of public transit disruption on the use of bike sharing (Fuller et al. 2012; Saberi et al. 2018; Kaviti et al. 2018; Younes et al. 2019). The first two studies focus on the impact of London underground strikes on bike sharing mobility patterns, and both of them found that the significant increase was observed in daily bike sharing trip counts and duration during each strike period. As we focus on planned transit closures which have completely different nature compared to strikes in that each surge at least lasts for 7 days instead of a single day, and maintenance activities only affect partial stations and area, our results are not comparable to theirs.

Kaviti et al. (2018) employed paired t-test simple linear regression model to analyze how disruptions to metro service impact the bike sharing ridership in the event of the concurrency of the launch of single-trip fare (STF) product with SafeTrack operations (refer to Section 3.1). However, they did not distinguish the impacts of different kinds of temporary public transit closure – continuous single-tracking (CST), referring to line closure in a certain direction, and line segment shutdowns (LSS), referring to line closure in in both directions. Also, this paper failed to consider the presence of planned disruptions in the regression model which only considered the week-long period before, during and after each surge, as well as ignored weekend trips and observations during experiences of precipitation. Younes et al. (2019) analyzed the impacts of three transit disruptions in SafeTrack project (surge 2, 4 and 10, refer to Supplementary Table 1) on bike sharing use employing autoregressive Poisson model. Nevertheless, they failed to capture the overdispersion characteristics of trips data and to identify impacts of various influential radii and biking distance on bike sharing demand in the event of transit closure, as well as to consider the impact of precipitation. Furthermore, average temperature used in their model is not a suitable indicator to measure the nonlinear relationship between bike sharing ridership and temperature.

To summarize, the key contributions of this paper includes: (1) this paper enriches existing research on the SafeTrack project with further analysis of the impact of influential radii, biking distance and maintenance type, which could provide clear guidance to transit agencies to take appropriate actions to increase transport resilience; (2) this paper adopts the difference between daily average temperature and optimum temperature as an indicator to capture the nonlinear relationship between temperature and bike sharing use, instead of mean temperature or maximum temperature which is commonly used in previous literature; (3) this paper shows that the proximity of bike sharing docks to metro stations appears to have a powerful effect on propensity to use a bike sharing program, which encourages planners and policymakers to account for coherence of traditional public transport modes and emerging transit modes to stimulate the development of eco-friendly mobility.

3 Methodology and Data Sources

3.1 A Case Study of Washington, DC

In this study, we focus on the changes in bike sharing ridership during “SafeTrack” project. This is an accelerated track work plan, occurring between 2016 and 2017, initiated by Washington Metropolitan Area Transit Authority (WMATA) to address safety

recommendations of Federal Transit Administration and National Transportation Safety Board while restoring track infrastructure to good health (WMATA 2017). It consists of 16 surges taking place in the Washington, D.C. metropolitan area in urban centers and suburban hubs, dividing into two kinds of temporary public transit closure – CST and LSS. This study will separately explore the impacts of CST and LSS on bike sharing ridership based on 12 of 16 surges (surge 8, 9, 11 and 14 are excluded from analysis due to the absence of bike sharing docks around affected metro stations) to identify the influences of different types of transport disruptions. Supplementary Table 1 summarizes the date, duration, affected metro lines, stations and area, as well as the maintenance type of each surge and Supplementary Fig. 1 visualizes affected metro lines and stations.

This study uses Capital Bike Sharing trip history data (Capital Bikeshare 2019) from 1st January 2015 to 31st December 2017 to investigate changes in bike sharing ridership during each planned disruption of transit service, which includes duration, start and end date, origination and destination, as well as member type. This dataset is especially useful as it covers bike sharing usage of the total population in Washington, D.C., allowing us to overcome sampling errors. The data has also been processed to remove trips that are taken by staff as they service and inspect the system and any trips lasting less than 60 s due to potentially false starts or users trying to re-dock a bike to ensure it is secure (Bao et al. 2017). Due to data limitations we do not have any information about trip purpose; our analysis is based on the assumption that any bike sharing trips within the influential radius of metro stations are either to substitute for the metro or to facilitate the use of the metro.

3.2 Methodology

The main research objectives in this paper are (1) to measure and quantify the impact of transit closure on bike sharing use; (2) to differentiate this impact across different maintenance type, influential radii and biking distance. We use an autoregressive negative binomial time series model to address these questions.

The Breusch-Godfrey test ($p = 0.0000$) and the Box-Pierce Q test ($p = 0.0000$) strongly indicate that time dependency in daily trips exists. For count series data, there are problems with using linear regression model to analyze these data. The linear regression model has the wrong model for both the relationship between the predictors and the expected values of the counts and the relationship between the expected values and the variance of the counts. It may therefore lead to misleading inferences about the predictors. The Poisson regression model is defined by a highly restrictive model for the variance of the dependent variable, which is suitable for data with equi-dispersion characteristics. Otherwise, badly misleading conclusions might be drawn (Gardner et al. 1995). Based on the nature of the issue and the characteristics of the data (which is overdispersion), the most suitable model is an autoregressive negative binomial time series model, which is listed in formula (1):

$$y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 \text{weather}_t + \beta_3 \text{stf}_t + \beta_4 \text{surge}_t + \beta_5 \text{nonwork}_t + \beta_6 \text{nonschool}_t + \varepsilon_t, \quad (1)$$

where t denotes time in days. Specifically, the variable y_t denotes daily trip counts, which are derived by aggregating data on the trip counts for that day up to the bike sharing dock-level. The variable y_{t-1} denotes autoregressive terms. We use three

autoregressive terms to capture both short-term and long-term effects: one-day lag, one-week lag, and one-year lag. To control for seasonality, a series of weather variables ($weather_t$) are included in analysis, including the absolute value of deviation between mean temperature and appropriate temperature (hereafter referred to as temp deviation), mean temperature, maximum wind speed, precipitation, snow depth and visibility. We obtained these weather variables from Weather Online (Weather Online 2019). Huntington (1922) has presented curves showing optimal temperature for the activities of lower organisms as well as of humans. The appropriate temperature used in this paper is the one which is optimal for the combination of mental and physical energy suggested by this curve. Dummy variables are used to control for the introduction of STF (a fare product aimed at casual users introduced in June 2016), non-workdays (weekends and holidays) and non-school days (mid-June to end of August, and mid-December to early January). A dummy variable indicating the presence of each surge is used as the intervening variable.

In ArcGIS, to sort out the bike sharing docks potentially impacted by SafeTrack surges, we filtered all bike sharing docks within a set of buffers (0–0.25mile, 0.25–0.5mile, 0.5–0.75 mile) of the shutdown metro stations using Multiple Ring Buffer and Spatial Join tools. Then we created Python functions to find possible pairs of filtered bike sharing docks connecting affected metro stations, which implied alternative ways of travel by bike during the surges. Finally, we conducted Network Analysis to calculate the shortest network distance for each bike sharing dock pair based on the cycling road network.

We aggregate daily bike sharing trips between docks around affected metro stations by different influential radii to carry out influential radii analysis. After that, the daily ridership of bike sharing is re-aggregated by biking distance to explore the impact of biking distance on shared bike use. These results are found to be robust in a series of robustness checks, such as shorten sample window, monthly bike sharing trip data (instead of daily data) and sub-sample analysis, which help to solve the concerns about both the length of the sample time span and the noisy daily data.

4 Results and Discussions

4.1 Influential Radii Analysis

Using the Geographic Information System (GIS) tools, bike sharing docks falling within the 0.25/0.5/0.75 mile radius of those Metro stations were isolated for SafeTrack impact analysis (Supplementary Fig. 2). Table 1 presents the analytical results of negative binomial model and autoregressive negative binomial model by maintenance type with an influential radius of 0.25 mile. Both Akaike Information Criterion (AIC) and log likelihood coefficient show that autoregressive negative binomial model outperforms negative binomial model with no autoregressive terms. Most of time lags are statistically significant indicating the dependency nature of daily trips data on past values. The impacts of weather variables are highly consistent regardless of maintenance type. The greater the temp deviation, the greater the negative impact on daily trips, which is also in line with the nonlinear relationship between temperature and bike sharing trips count. Mean temperature and visibility have positive and significant

Table 1 Results of time series analysis by maintenance type with an influential radius of 0.25 mile

Dependent variable: daily trip counts	(1) LSS	(2) LSS	(3) IRR	(4) CST	(5) CST	(6) IRR
One-day lag	N/A	0.007*** (0.001)	1.007	N/A	0.037*** (0.009)	1.038
One-week lag	N/A	0.003*** (0.001)	1.003	N/A	0.035*** (0.008)	1.035
One-year lag	N/A	0.002** (0.001)	1.002	N/A	-0.009 (0.010)	0.991
Temp deviation	-0.018*** (0.003)	-0.018*** (0.004)	0.982	-0.018** (0.008)	-0.024** (0.010)	0.977
Mean temp	0.044*** (0.002)	0.035*** (0.003)	1.036	0.055*** (0.006)	0.045*** (0.007)	1.046
Max wind speed	-0.008*** (0.002)	-0.006** (0.003)	0.994	-0.010* (0.005)	-0.011* (0.006)	0.989
Precipitation	-0.282*** (0.063)	-0.352*** (0.076)	0.704	-0.426** (0.181)	-0.537** (0.240)	0.585
Snow depth	-0.176*** (0.035)	-0.233*** (0.059)	0.792	-0.148* (0.081)	-0.261* (0.145)	0.770
Visibility	0.126*** (0.018)	0.098*** (0.022)	1.103	0.165*** (0.042)	0.119** (0.050)	1.126
Presence of STF	0.005 (0.022)	-0.081** (0.035)	0.922	1.001*** (0.053)	1.071*** (0.122)	2.917
Non-work days	-0.106*** (0.024)	-0.155*** (0.029)	0.856	-0.252*** (0.061)	-0.305*** (0.074)	0.737
Presence of surge	0.256*** (0.037)	0.194*** (0.035)	1.214	-0.106 (0.080)	-0.045 (0.083)	0.956
Non-school days	-0.096*** (0.029)	-0.073** (0.032)	0.930	-0.033 (0.063)	-0.006 (0.078)	0.994
Constant	1.557*** (0.169)	1.720*** (0.205)	5.584	-1.807*** (0.408)	-1.458*** (0.494)	0.233
Observations	1096	731	N/A	1096	731	N/A
Pseudo R ²	0.123	0.135	N/A	0.145	0.144	N/A
AIC	7554.808	5020.665	N/A	4030.442	2921.845	N/A
Log likelihood	-3765.4042	-2495.3325	N/A	-2003.221	-1445.9227	N/A

Note: IRR means incidence rate ratio

Standard errors are in parenthesis

***** $p < 0.1$, ** $p < 0.05$, * $p < 0.01$

effects on bike sharing trips, while wind speed, precipitation and snow depth hinders bike sharing trips. These weather effects are consistent with previous literature (Guo et al. 2007; Colls et al. 2010; Younes et al. 2019). The coefficients of non-work days are negative and significant for both LSS and CST, showing that purpose of most trips

is to commute rather than leisure. The coefficients of non-school days are negative and only significant for LSS, meaning that most of affected zones for complete metro lines shutdown are not tourist attractions. It is worth noting that the intervening variable has a significant and positive impact merely in the case of LSS, indicating that people prefer to consider bike sharing as an alternative mode of travel when the metro tracks are completely closed.

The regression results with an influential radius of 0.5 mile are reported in Table 2. In a series of weather variables, precipitation has the greatest impact on bike sharing daily trips, which increases by one unit will result in more than 30% decrease in bike-sharing daily trips (third and sixth columns in Table 2). In addition, snow depth and temp deviation will reduce daily trips by more than 20% and 2%, while visibility increase daily trips by nearly 8%. These results indicated that weather conditions and safety concerns are important factors to consider when individuals weigh in on modes of travel. Bike sharing trips on weekends decrease by 12.5% compared to that on weekdays, verifying again that most of bike sharing users are commuters. There is an increase of 7.5% in bike sharing trips observed in LSS, indicating that redistribution activities should give priority to bike sharing docks around affected metro stations to better meet the needs of transit users and to optimize the usage of bike sharing in the event of complete transit closure.

Table 3 shows the analytical results of negative binomial model and autoregressive negative binomial model for 0.75 mile. By comparing IRR of regression results of various influential radii, we find that the magnitude of most variables decreases as influential radii increases, although it is still statistically significant. This shows that the better the connection between traditional public transport modes and emerging transit modes, the more encouraging the development of eco-friendly travel modes. This also urges planners and policymakers to account for the interdependence between demand and supply of bike sharing in reallocation activities (Jian et al. 2019). The coefficient of the intervening variable is still strongly significant in the analysis of 0.75 mile indicating that the influential radius of SafeTrack project on the bike sharing use is at least 0.75 mile. This provides guidance for temporary remedy measures taken by transit agency in response to public transport closure.

4.2 Biking Distance Analysis

The above analytical results indicate that CST do not have practically meaningful impacts on bike sharing daily trips and thus were excluded from the following analysis. To better capture the impact of biking distance on bike sharing demand, we chose network distance to estimate biking distance, which depends on the actual length of road and travelling experience structured by the road hierarchy and obstacles for shortest path routing, instead of Euclidean distance used in previous study. We divide biking distance into three groups: 0–2 miles, 2–4 miles and 4–6 miles.

The results of our time series analysis of biking distance are reported in Table 4. For a range of weather variables, there is a clear trend that the impact of weather on bike sharing use increases with biking distance, indicating that safety and comfort concerns are important factors for users to consider. Planners can boost the use of bike sharing by improving its safety and comfort. Among them, precipitation and snow depth have significant negative impacts on bike sharing trips, which indicate that individuals tend to choose motorized modes, such as public bus or private vehicles, in the event of

Table 2 Results of time series analysis by maintenance type with an influential radius of 0.5 mile

Dependent variable: daily trip counts	(1) LSS	(2) LSS	(3) IRR	(4) CST	(5) CST	(6) IRR
One-day lag	N/A	0.001*** (0.000)	1.001	N/A	0.025*** (0.006)	1.025
One-week lag	N/A	0.001*** (0.000)	1.001	N/A	0.015*** (0.005)	1.016
One-year lag	N/A	0.001*** (0.000)	1.001	N/A	-0.002 (0.006)	0.998
Temp deviation	-0.012*** (0.002)	-0.014*** (0.003)	0.986	-0.014** (0.006)	-0.024*** (0.007)	0.976
Mean temperature	0.040*** (0.001)	0.032*** (0.002)	1.033	0.049*** (0.004)	0.046*** (0.005)	1.047
Max wind speed	-0.006*** (0.002)	-0.004** (0.002)	0.996	-0.010** (0.004)	-0.010** (0.004)	0.990
Precipitation	-0.269*** (0.042)	-0.343*** (0.059)	0.709	-0.386*** (0.105)	-0.549*** (0.150)	0.578
Snow depth	-0.164*** (0.033)	-0.214*** (0.054)	0.807	-0.172*** (0.066)	-0.322*** (0.121)	0.724
Visibility	0.108*** (0.013)	0.080*** (0.017)	1.083	0.139*** (0.029)	0.082** (0.037)	1.085
Presence of STF	0.032** (0.015)	-0.026 (0.023)	0.974	0.659*** (0.038)	0.601*** (0.076)	1.824
Non-work days	-0.093*** (0.017)	-0.134*** (0.020)	0.875	-0.343*** (0.044)	-0.345*** (0.054)	0.708
Presence of surge	0.088*** (0.020)	0.073*** (0.020)	1.075	-0.079 (0.062)	-0.031 (0.065)	0.969
Non-school days	-0.102*** (0.023)	-0.078*** (0.025)	0.925	-0.015 (0.045)	0.013 (0.057)	1.013
Constant	3.304*** (0.124)	3.387*** (0.160)	29.585	-0.730*** (0.281)	-0.210 (0.367)	0.811
Observations	1096	731	N/A	1096	731	N/A
Pseudo R ²	0.125	0.139	N/A	0.150	0.154	N/A
AIC	10,310.092	6824.477	N/A	4686.906	3290.816	N/A
Log likelihood	-5143.0458	-3397.2383	N/A	-2331.453	-1630.4081	N/A

Note: IRR means incidence rate ratio

Standard errors are in parenthesis

*****p < 0.1, p < 0.05, p < 0.01

extreme weather. For those dummy variables indicating holidays and weekends, the most significant negative influence is observed in 2–4 miles group. If we consider fare products of bike sharing, this result is not surprising. There are five most popular fare products adopted by bike sharing users in Washington, D.C., including single trip, 24-h

Table 3 Results of time series analysis by maintenance type with an influential radius of 0.75 mile

Dependent variable: daily trip counts	(1) LSS	(2) LSS	(3) IRR	(4) CST	(5) CST	(6) IRR
One-day lag	N/A	0.000*** (0.000)	1.000	N/A	0.003** (0.001)	1.003
One-week lag	N/A	0.000*** (0.000)	1.000	N/A	0.003** (0.001)	1.003
One-year lag	N/A	0.000** (0.000)	1.000	N/A	0.001 (0.001)	1.001
Temp deviation	-0.008*** (0.002)	-0.010*** (0.003)	0.990	-0.013*** (0.003)	-0.018*** (0.004)	0.983
Mean temperature	0.038*** (0.001)	0.030*** (0.002)	1.031	0.042*** (0.002)	0.037*** (0.003)	1.038
Max wind speed	-0.005*** (0.002)	-0.003 (0.002)	0.997	-0.003 (0.002)	-0.002 (0.003)	0.998
Precipitation	-0.282*** (0.037)	-0.370*** (0.050)	0.691	-0.350*** (0.055)	-0.453*** (0.090)	0.636
Snow depth	-0.184*** (0.036)	-0.219*** (0.054)	0.803	-0.183*** (0.046)	-0.235*** (0.085)	0.791
Visibility	0.091*** (0.013)	0.059*** (0.020)	1.061	0.116*** (0.017)	0.082*** (0.023)	1.086
Presence of STF	-0.058*** (0.015)	-0.089*** (0.023)	0.915	0.393*** (0.024)	0.379*** (0.046)	1.461
Non-work days	-0.329*** (0.017)	-0.307*** (0.022)	0.736	-0.510*** (0.029)	-0.466*** (0.038)	0.628
Presence of surge	0.061*** (0.020)	0.055*** (0.020)	1.057	-0.080** (0.040)	-0.049 (0.040)	0.952
Non-school days	-0.123*** (0.024)	-0.088*** (0.027)	0.915	-0.094*** (0.031)	-0.062* (0.037)	0.940
Constant	4.864*** (0.123)	4.913*** (0.176)	136.095	1.514*** (0.163)	1.746*** (0.219)	5.729
Observations	1096	731	N/A	1096	731	N/A
Pseudo R ²	0.102	0.108	N/A	0.132	0.134	N/A
AIC	13,123.158	8745.682	N/A	7731.362	5260.271	N/A
Log likelihood	-6549.5788	-4357.8409	N/A	-3853.681	-2615.1353	N/A

Note: IRR means incidence rate ratio

Standard errors are in parenthesis

***** $P < 0.1$, $p < 0.05$, $P < 0.01$

pass, 3-day pass, monthly pass and annual pass. All fare products except the single trip offer unlimited trips for rides under 30-min duration. If a rider exceeds 30-min of bike usage, a usage fee is assessed. According to biking speed calculated by Virkler (1998), biking distance which exceeds 4 miles requires more than 30-mins in some cases,

Table 4 Results of time series analysis by biking distance

Dependent variable: daily rip counts	(1) 0–2 miles	(2) IRR	(3) 2–4 miles	(4) IRR	(5) 4–6 miles	(6) IRR
One-day lag	0.001*** (0.000)	1.001	0.010*** (0.002)	1.010	0.017 (0.018)	1.018
One-week lag	0.000*** (0.000)	1.000	0.007*** (0.002)	1.007	0.005 (0.015)	1.005
One-year lag	0.000* (0.000)	1.000	0.001 (0.002)	1.001	0.015 (0.017)	1.015
Temp deviation	-0.009*** (0.003)	0.991	-0.043*** (0.005)	0.958	-0.058*** (0.021)	0.944
Mean temperature	0.029*** (0.002)	1.030	0.053*** (0.004)	1.055	0.089*** (0.016)	1.093
Max wind speed	-0.002 (0.002)	0.998	-0.011*** (0.003)	0.989	-0.018* (0.009)	0.982
Precipitation	-0.361*** (0.050)	0.697	-0.480*** (0.092)	0.619	-0.838*** (0.223)	0.433
Snow depth	-0.218*** (0.053)	0.804	-0.237** (0.115)	0.789	-0.490** (0.234)	0.613
Visibility	0.060*** (0.020)	1.062	0.093*** (0.027)	1.097	0.143* (0.074)	1.154
Presence of STF	-0.090*** (0.023)	0.914	0.156*** (0.048)	1.168	0.228 (0.147)	1.256
Non-work days	-0.305*** (0.022)	0.737	-0.337*** (0.037)	0.714	0.269*** (0.096)	1.309
Presence of surge	0.008 (0.024)	1.008	0.023 (0.048)	1.023	-0.089 (0.129)	0.915
Non-school days	-0.081*** (0.027)	0.922	-0.136*** (0.043)	0.873	-0.089 (0.125)	0.914
Constant	4.856*** (0.172)	128.570	1.347*** (0.265)	3.846	-1.740** (0.712)	0.175
Observations	731	N/A	731	N/A	731	N/A
Pseudo R ²	0.108	N/A	0.143	N/A	0.074	N/A
AIC	8670.960	N/A	4806.720	N/A	2571.222	N/A
Log likelihood	-4320.4798	N/A	-2388.36	N/A	-1270.6111	N/A

Note: IRR means incidence rate ratio

Standard errors are in parenthesis

*****p < 0.1, p < 0.05, p < 0.01

which requires a usage fee in addition to the membership fee. Considering most users are commuters in peak hour, biking time may exceed 30-min with biking distances close to 4 miles. This indicates that cost is another crucial factor influencing users' choice. The variable indicating presence of surge is not significant in all three groups,

which shows that its impact on bike sharing usage have little to do with biking distance but closely related with maintenance type.

Considering affected metro stations are distributed across a large area, we divide the full sample into two sub-samples (central areas and outer districts) to explore the impact of traffic conditions on bike sharing usage. Central areas refer to regions within the Washington, D.C. boundary, while outer districts refer to areas outside the Washington, D.C. boundary. The empirical results (Supplementary Table 2) indicate that bike sharing trips on central areas increase by 10.1% during the period of public transit disruption, while the ridership of shared bike in outer areas increase by 11.4% when surge occurs. We find that traffic conditions do not contribute to significant differences in bike sharing ridership among regions in the case of public transit disruption.

5 Robustness Test

5.1 Shorter Window Sample

Owing to the long span of the whole sample and the short time of surges, we adjust the time bandwidth to further identify whether the impact of surges on bike sharing usage changes significantly with the length of the sample time span (Yang et al. 2019). The period without surges should be appropriately shortened in order to avoid other possible overlooked interference factors. On this basis, the robustness of results can be tested by changing the sample window. Samples of each surge during the occurrence and 30 days before and after the surge are retained for a second time of autoregressive negative binomial analysis in an attempt to eliminate other possible interfering factors and ensure the validity of our results. As shown in Table 5, after changing sample window length, the variable of concern (*presence of surge*) and other weather variables still significant and hold the same signs with previous results. At this point, it is reasonable to believe that our previous conclusions are robust and valid.

5.2 Monthly Data

The daily bike sharing trips data can be noisy due to changeable weather conditions and constantly updated docks. Thus, we also aggregate our data to monthly level to check the robustness of our results (Liu and Shi 2018). The results from the regression using monthly data are reported in Table 6. They are similar to what we found earlier from daily data, including signs and trends, which lend strong support to earlier analysis results. In the regression using monthly data, the magnitude of coefficients of the intervening variable (*presence of surge*) are quantitatively smaller than that in the regression using daily data. This can be explained by the fact that most surges last no more than 2 weeks, thereby using monthly data may underestimate the impact of surges on bike sharing demand.

5.3 Sub-Sample Test

The results of full sample robustness test still support our conclusion that bike sharing can enhance urban transport resilience. We then perform a sub-sample robustness test based on weather variables to examine the above conclusion. Weather conditions,

Table 5 Results of time series analysis based on short sample window

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)
daily trip counts	0.25 LSS	0.25 CST	0.5 LSS	0.5 CST	0.75 LSS	0.75 CST
One-day lag	0.008*** (0.002)	0.039*** (0.011)	0.001*** (0.000)	0.022*** (0.008)	0.000*** (0.000)	0.003*** (0.001)
One-week lag	0.004** (0.002)	0.024** (0.010)	0.001*** (0.000)	0.009 (0.007)	0.000*** (0.000)	0.002* (0.001)
Temp deviation	-0.017*** (0.007)	-0.032** (0.015)	-0.014*** (0.004)	-0.026** (0.011)	-0.013*** (0.004)	-0.025*** (0.006)
Mean temperature	0.036*** (0.005)	0.051*** (0.010)	0.032*** (0.003)	0.051*** (0.008)	0.033*** (0.003)	0.043*** (0.004)
Max wind speed	-0.009** (0.004)	-0.012* (0.007)	-0.004* (0.002)	-0.011** (0.005)	-0.004 (0.002)	-0.006 (0.003)
Precipitation	-0.210** (0.089)	-0.818*** (0.179)	-0.256*** (0.075)	-0.581*** (0.140)	-0.296*** (0.060)	-0.516*** (0.078)
Snow depth	-0.094 (0.109)	0.131 (0.368)	-0.149* (0.083)	0.327 (0.204)	-0.080 (0.106)	0.156 (0.120)
Visibility	0.143*** (0.033)	0.138** (0.069)	0.114*** (0.026)	0.145*** (0.053)	0.095*** (0.025)	0.107*** (0.033)
Presence of STF	0.099 (0.080)	0.663* (0.352)	0.069 (0.061)	0.680*** (0.245)	0.066* (0.032)	0.472*** (0.119)
Non-work days	-0.184*** (0.036)	-0.272*** (0.094)	-0.145*** (0.024)	-0.329*** (0.070)	-0.286*** (0.027)	-0.436*** (0.046)
Presence of surge	0.186*** (0.038)	0.014 (0.087)	0.084*** (0.022)	-0.002 (0.069)	0.065*** (0.021)	-0.031 (0.039)
Non-school days	-0.082* (0.044)	0.103 (0.107)	-0.072** (0.033)	0.043 (0.077)	-0.095*** (0.035)	-0.056 (0.045)
Constant	1.144*** (0.338)	-1.328* (0.760)	3.031*** (0.265)	-0.986* (0.575)	4.427*** (0.251)	1.412*** (0.359)
Observations	420	420	420	420	420	421
Pseudo R ²	0.124	0.090	0.121	0.113	0.107	0.115
AIC	2952.429	1842.247	3938.185	2008.260	4956.988	3062.085
Log likelihood	-1462.2147	-907.12372	-1955.0926	-990.12986	-2464.4941	-1517.0427

Standard errors are in parenthesis

*****p < 0.1, p < 0.05, p < 0.01

especially precipitation, directly and constantly affect individuals’ travel choices (Guo et al. 2007; Aultman-Hall et al. 2009; Cools et al. 2010). Affected transit riders may react by adjusting their departure times, travel modes and destinations or by canceling trips. We divide the full sample into 12 groups according to total daily precipitation and maintenance type. Regression results using sub-sample data are reported in Table 7. They are similar to what we found earlier using full sample data. At this point, it is reasonable to believe that our previous conclusion is robust and valid.

Table 6 Results of time series analysis based on monthly data

Dependent variable: (1)	(2)	(3)	(4)	(5)	(6)	
monthly trip counts	0.25LSS	0.25CST	0.5LSS	0.5CST	0.75LSS	0.75CST
One-month lag	0.008*** (0.001)	0.045*** (0.008)	0.002*** (0.000)	0.029*** (0.006)	0.001*** (0.000)	0.005*** (0.001)
One-year lag	0.001 (0.001)	0.029*** (0.008)	0.000 (0.000)	0.014*** (0.005)	0.000*** (0.000)	0.004*** (0.001)
Temp deviation	-0.017*** (0.003)	-0.019** (0.008)	-0.013*** (0.002)	-0.016*** (0.006)	-0.009*** (0.002)	-0.014*** (0.003)
Mean temperature	0.037*** (0.002)	0.047*** (0.006)	0.033*** (0.002)	0.042*** (0.004)	0.029*** (0.002)	0.035*** (0.002)
Max wind speed	-0.006*** (0.002)	-0.010* (0.005)	-0.005*** (0.001)	-0.009** (0.004)	-0.004*** (0.001)	-0.002 (0.002)
Precipitation	-0.291*** (0.063)	-0.459*** (0.166)	-0.283*** (0.042)	-0.405*** (0.100)	-0.299*** (0.037)	-0.386*** (0.054)
Snow depth	-0.166*** (0.034)	-0.157* (0.081)	-0.155*** (0.031)	-0.176*** (0.066)	-0.175*** (0.034)	-0.181*** (0.044)
Visibility	0.113*** (0.017)	0.152*** (0.042)	0.097*** (0.013)	0.127*** (0.029)	0.080*** (0.013)	0.102*** (0.017)
Presence of STF	-0.007 (0.021)	0.800*** (0.063)	0.011 (0.016)	0.525*** (0.045)	-0.061*** (0.014)	0.293*** (0.030)
Non-work days	-0.107*** (0.024)	-0.222*** (0.062)	-0.092*** (0.017)	-0.316*** (0.044)	-0.312*** (0.017)	-0.506*** (0.030)
Presence of surge	0.191*** (0.035)	-0.077 (0.081)	0.069*** (0.020)	-0.051 (0.063)	0.054*** (0.019)	-0.043 (0.041)
Non-school days	-0.080*** (0.027)	-0.046 (0.062)	-0.079*** (0.021)	-0.025 (0.044)	-0.097*** (0.022)	-0.073** (0.030)
Constant	1.547*** (0.166)	-1.657*** (0.412)	3.276*** (0.121)	-0.629** (0.283)	4.779*** (0.116)	1.548*** (0.160)
Observations	1096	1096	1096	1096	1096	1096
Pseudo R ²	0.129	0.153	0.129	0.156	0.107	0.136
AIC	7508.347	3994.082	10,257.195	4655.465	13,052.003	7697.842
Log likelihood	-3740.1736	-1983.041	-5114.5973	-2313.7326	-6512.0017	-3834.921

Standard errors are in parenthesis

***** $p < 0.1$, ** $p < 0.05$, * $p < 0.01$

6 Conclusions

This study explores the effect of public transit closures on bike sharing demand during the SafeTrack project period initiated by WMATA. This study enriches extant research by discussing impacts of maintenance type and biking distance on bike sharing usage, as well as identifying the maximum influential radius of temporary transit closure. Our analysis suggests that the influence of transit disruption on bike sharing demand

Table 7 Results of time series analysis based on sub-sample

Dependent variable: daily trip counts	(1) 0.25 LSS precipitation=0 -0.021*** (0.003)	(2) 0.25 LSS precipitation>0 -0.018*** (0.009)	(3) 0.5 LSS precipitation=0 -0.016*** (0.002)	(4) 0.5 LSS precipitation>0 -0.011* (0.007)	(5) 0.75 LSS precipitation=0 -0.013*** (0.002)	(6) 0.75 LSS precipitation>0 -0.011** (0.006)
Temp deviation	0.045*** (0.002)	0.048*** (0.007)	0.041*** (0.001)	0.041*** (0.005)	0.039*** (0.001)	0.042*** (0.004)
Mean temperature	-0.009*** (0.003)	-0.002 (0.004)	-0.005*** (0.002)	-0.005 (0.003)	-0.005*** (0.002)	-0.003 (0.003)
Max wind speed	-0.135*** (0.040)	-0.047 (0.062)	-0.153*** (0.048)	-0.035 (0.046)	-0.147*** (0.044)	-0.040 (0.051)
Snow depth	0.062*** (0.022)	0.139*** (0.024)	0.044*** (0.014)	0.147*** (0.017)	0.036*** (0.012)	0.129*** (0.016)
Visibility	0.011 (0.022)	0.013 (0.054)	0.033** (0.015)	0.038 (0.039)	-0.054*** (0.015)	-0.055 (0.038)
Presence of STF	-0.114*** (0.026)	-0.048 (0.054)	-0.088*** (0.017)	-0.108** (0.042)	-0.316*** (0.018)	-0.369*** (0.042)
Non-work days	0.260*** (0.040)	0.232*** (0.073)	0.083*** (0.021)	0.120** (0.049)	0.048** (0.020)	0.117** (0.049)
Presence of surge	-0.120*** (0.030)	0.013 (0.076)	-0.119*** (0.023)	-0.056 (0.064)	-0.138*** (0.025)	-0.079 (0.062)
Non-school days	2.248*** (0.216)	1.060*** (0.215)	3.964*** (0.139)	2.746*** (0.160)	5.443*** (0.113)	4.285*** (0.155)
Constant	818 (0.114)	269 (0.114)	821 (0.124)	271 (0.106)	821 (0.102)	271 (0.090)
Observations	-2809.2753 (7)	-893.58286 (8)	-3799.2228 (9)	-1267.5143 (10)	-4841.1229 (11)	-1610.0397 (12)
Pseudo R ²						
Log likelihood						
Dependent variable: daily trip count					0.75 CST precipitation=0	

Table 7 (continued)

	0.25 CST precipitation = 0	0.25 CST precipitation > 0	0.5 CST precipitation = 0	0.5 CST precipitation > 0	0.75 CST precipitation > 0
Temp deviation	-0.030** (0.012)	-0.011 (0.027)	-0.022*** (0.007)	-0.010 (0.017)	-0.018*** (0.003)
Mean temperature	0.058*** (0.009)	0.050** (0.022)	0.049*** (0.005)	0.043*** (0.013)	0.036*** (0.006)
Max wind speed	-0.010 (0.007)	-0.006 (0.010)	-0.012*** (0.004)	-0.001 (0.008)	0.003 (0.005)
Snow depth	-0.549 (0.411)	0.159 (0.227)	-0.241 (0.245)	0.189 (0.147)	-0.158** (0.064)
Visibility	0.036 (0.069)	0.236*** (0.089)	0.083* (0.046)	0.221*** (0.053)	0.071*** (0.022)
Presence of STF	1.048*** (0.073)	1.042*** (0.148)	0.675*** (0.043)	0.639*** (0.096)	0.412*** (0.060)
Non-work days	-0.221*** (0.077)	-0.333** (0.162)	-0.288*** (0.049)	-0.437*** (0.124)	-0.614*** (0.066)
Presence of surge	-0.165* (0.093)	-0.053 (0.163)	-0.100 (0.066)	0.031 (0.132)	-0.208*** (0.080)
Non-school days	0.042 (0.076)	-0.244 (0.178)	0.033 (0.050)	0.048 (0.128)	-0.067 (0.084)
Constant	-0.512 (0.704)	-2.534*** (0.833)	-0.066 (0.461)	-1.771*** (0.487)	1.075*** (0.227)
Observations	657	174	744	233	268
Pseudo R ²	0.113	0.138	0.128	0.145	0.117
Log likelihood	-1246.3361	-279.74655	-1608.688	-423.68305	-2879.0904

Standard errors are in parenthesis.

****p < 0.1, p < 0.05, p < 0.01

depends on maintenance type. The slowdown caused by LSS surges do meaningfully impact bike sharing trips, and this impact weakens as the influential radius increases. This is an important finding as it shows that the proximity of bike sharing docks to metro stations tends to have a powerful effect on propensity to use bike sharing programs. The influential radius of transit disruptions is at least 0.75 miles. This is a meaningful finding as it provides guidance for planners and bike sharing firms to distribute and rebalance bikes in the case of planned maintenance work. Weekday ridership increased more than weekend ridership, which indicates the likelihood that these are commuters rather than leisure trips. Results of biking distance analysis indicate that security and cost concerns are major barriers to bicycling. Planners can boost the use of bike sharing by strengthening the maintenance and overhaul of bikes, providing helmets and providing various fare products.

From the perspective of achieving eco-friendly mobility, planned transit disruption provides evidence that rapid changes to transport policy and travel patterns is possible. Promoting bike sharing can be considered as a useful strategy to accelerate needed changes in personal transportation choices thereby fostering structural change towards sustainable economies. Recommendations for bike sharing management and development are to (1) take capacity and usage of bike sharing docks into consideration when distributing and rebalancing bikes to maximize and optimize its use, especially in the case of transit disruptions when people have to switch transit modes; (2) account for coherence of metro stations and bike sharing docks to boost the use of eco-friendly transportation choices; and (3) improve safety and comfort of bike sharing to break down barriers to bike sharing use.

Future research could focus on the analysis of the socioeconomic details of transit users, as well as trip characteristics, and how these differences affect users' choices in transit modes during transit closure. This would provide information to planners on how to design urban transportation systems to make them more resilient, inclusive, and better able to cope with natural and man-made emergencies. This type of analysis can be applied to other cities which plan to undertake public transit maintenance work or have already gone through such work to better understand attitudinal preferences towards a modal shift by transit users.

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