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How transit service closures influence bikesharing demand; lessons learned from SafeTrack project in Washington, D.C. metropolitan area

Hannah Younes[a,c,*], Arefeh Nasri[b], Giovanni Baiocchi[c], Lei Zhang[a]

[a] Maryland Transportation Institute, University of Maryland, 3244 Jeong H. Kim Engineering Building, 8228 Paint Branch Dr., College Park, MD 20742, United States
[b] National Center for Smart Growth Research and Education, University of Maryland, College Park, United States
[c] Department of Geographical Sciences, University of Maryland, College Park, United States

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ABSTRACT

Transportation disruptions offer opportunities to study how people adapt to using new modes of transportation and have important implications for transportation policy and planning. Bikeshare has emerged as a new popular mode of transportation in recent years as it offers a fast, easy, and reliable way to travel short distances, and for its convenience as a first- and last-mile mode to complement transit. It also offers many social, environmental, and health-related benefits and has the potential to promote low-carbon mobility. This study examines changes in bikeshare ridership due to rail transit closures in the Washington, D.C. area and investigates how promoting bikeshare systems in large metropolitan areas could be beneficial in cases of transit disruptions – regardless of the type, cause, and duration. We use disaggregate trip history data to analyze the impact of three different transit closures in 2016 lasting 7 to 25 days. The objective of this paper is to provide insight on how transit disruptions affect bikeshare use. An autoregressive Poisson time series model is used to estimate effects of transit closures on bikeshare activity. Kernel density estimation is applied to understand spatial changes in ridership from a week before, one year before, and after each closure. Results are compared both temporally and spatially and confirm that transit disruptions were associated with increased bikeshare ridership at the local level. Once the affected Metro stations reopened, bikeshare ridership returned to original levels. We conclude that when within 0.25 mile of a rail station and with a rail station spacing of < 3 miles, bikeshare can be used as a mechanism for low-carbon mobility to complement transit.

1. Introduction

Travel disruptions are becoming more commonplace due to the increasing need for maintenance of aging infrastructure, system failures, or natural disasters (Marsden and Docherty, 2013; Zhu et al., 2017). Research on travel behavior during a metro system closure has been limited. The majority of the research on transit disruptions focus on day-long transit strikes rather than longer transit service disruptions (Van Exel and Rietveld, 2001; Marsden and Docherty, 2013; Saberi et al., 2018). Disruptions are important to study because they provide a glimpse at new patterns of behavior that could be adopted (Marsden and Docherty, 2013). Bikeshare systems offer many potential benefits, such as flexible mobility, reduction in emissions and noise, increase in physical activity, reduced fuel use, and support for multi-modal transportation systems (Shaheen, 2016). They could be used as an alternative mode when transit disruptions occur, especially for short commute distances and in cases when a private automobile is not a time- or cost-efficient option. However, very few studies in the past have focused on the relationship between transit disruptions and mode shifts to bikeshare, and thus the relationship between long-term planned transit disruptions and bikeshare ridership is not fully understood. To the authors' knowledge, this study is the first to investigate the effects of planned, long-term transit closures on bikeshare ridership.

In Washington, D.C., 36% of residents report commuting by public transit, 13.7% walk and 4.6% commute by bike (U.S. Census Bureau, 2016). During transit service disruptions, affected travelers may react by adjusting their route, departure time, travel modes, destination, or by cancelling trips (Zhu et al., 2017). The potential shift towards low-carbon mobility is important to examine. In this study, we are interested in how bikeshare ridership patterns varied during different transit service disruptions. All transit disruptions occurred between 2016 and 2017 and lasted 7 to 42 days. The service changes, known as

* Corresponding author at: Maryland Transportation Institute, University of Maryland, 3244 Jeong H. Kim Engineering Building, 8228 Paint Branch Dr., College Park, MD 20742, United States.
E-mail addresses: hyounes@umd.edu (H. Younes), aanasri@umd.edu (A. Nasri).

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Table 1
Description of SafeTrack surges.

Surge number	Date	Duration	Lines	Impact	Area affected	Closed stations impacted	Bikeshare available at both stations? (within 0.1 mile)	Biking distance
1	June 4–16, 2016	13 days	Orange Line Silver Line	CST	East Falls Church to Ballston	East Falls Church to Ballston:	Yes	3.0 mi
2[a]	June 18–July 3, 2016	16 days	Orange Line Blue Line Silver Line	LSS	Eastern Market to Minnesota Ave & Benning Road	Minnesota to Stadium Armory: Stadium Armory to Potomac Ave: Potomac Ave to Eastern Market Station:	No No Yes	3.5 mi. 1 mi. 0.7 mi
3	July 5–11, 2016	7 days	Yellow Line Blue Line	LSS	National Airport to Braddock Road	National Airport to Braddock Road:	No	3.8 mi
4	July 12–18, 2016	7 days	Yellow Line Blue Line	LSS	Pentagon City to National Airport	National Airport to Crystal City: Crystal City to Pentagon City:	No Yes	1.3 mi. 0.8 mi
5	July 20–31, 2016	12 days	Orange Line Silver Line	CST	East Falls Church to Ballston	*See Surge 1*		
6[a]	August 1–7, 2016	7 days	Red Line	CST	Takoma to Silver Spring	Takoma to Silver Spring:	Yes	1.8 mi
7	August 9–21, 2016	13 days	Red Line	CST	Shady Grove to Twinbrook	Shady Grove to Rockville: Rockville to Twinbrook:	Yes No	4.1 mi. 2.5 mi.
8	August 27–September 11, 2016	16 days	Yellow Line Blue Line	CST	Franconia-Springfield to Van Dorn Street	Franconia-Springfield to Van Dorn Street	No	4.3 mi.
9	September 15–October 26, 2016	42 days	Orange Line	CST	Vienna to West Falls Church	Vienna to Dunn Loring-Merrifield Dunn Loring-Merrifield to Falls Church	No No	3.7 mi. 3.4 mi.
10[a]	October 29–November 22, 2016	25 days	Red Line	LSS	Fort Totten to NoMa	Fort Totten to Brookland CUA: Brookland CUA to Rhode Island Ave: Rhode Island Ave to Noma:	Yes Yes Yes	2.3 mi. 1.0 mi. 1.3 mi.
11	November 28–December 20, 2016	23 days	Orange Line Silver Line	CST	East Falls Church to West Falls Church	East Falls Church to West Falls Church:	No	2.6 mi.
12	February 11–28, 2017	18 days	Blue Line	LSS	Rosslyn to Pentagon	Rosslyn to Arlington Cemetery: Arlington Cemetery to Pentagon: Rosslyn to Pentagon:	No No No	2.3 mi. 2.2 mi. 3.5 mi.
13	March 4–April 12, 2017	40 days	Blue Line Yellow Line	CST	Braddock Rd to Huntington/Van Dorn St	Huntington to Eisenhower Avenue Eisenhower Avenue to King Street King Street to Braddock Road	No Yes Yes	1.4 mi. 1.1 mi. 0.9 mi.
14	April 15–May 14, 2017	30 days	Green Line	LSS	Greenbelt to College Park	Greenbelt to College Park:	No	
15[a]	May 16–June 15, 2017	31 days	Orange Line	LSS	New Carrollton to Stadium-Armory	*See Surge 2*		
16	June 17–25, 2017	9 days	Red Line	LSS	Shady Grove to Twinbrook	*See Surge 7*		

[a] Indicates that at least one impacted station is inside the D.C. boundaries.

"SafeTrack", were part of Washington Metropolitan Area Transit Authority's (WMATA) long-term project to address Federal Transit Administration (FTA) and National Transportation Safety Board (NTSB) safety recommendations, and to rehabilitate the Metrorail system to improve safety and reliability. The 16 planned disruptions, referred in this paper as *Surges*, involved either continuous single-tracking (CST) or closing tracks completely for one week or longer periods. These surges took place across the Washington, D.C. metropolitan area in urban centers and suburban hubs. In this analysis, only the results of surges that involved line segment shutdowns (LSS) – meaning that transit users could not use the rail at all – and had bikeshare available as a viable alternative mode of transportation are presented. Bikeshare is considered an alternative when it is available at two or more consecutive rail stations or two stations not spaced more than three-mile apart (a reasonable distance for biking). Three of the eight closed track surges and two of the eight continuous single-tracking surges qualified for this study, as seen in Table 1. An initial analysis indicated that the two continuous single-tracking surges did not have a practically meaningful impact bikeshare trips and thus were excluded from the body of this paper.

We use Capital Bikeshare Trip History data to assess ridership increases in bike use around affected rail stations (Capital Bikeshare, 2018). This analysis is beneficial in that it uses the entire population using bikeshare rather than a small sample. It overcomes errors associated with sampling and with self-reported survey data. Nonetheless, it has limitations in that there is no information available on bikeshare users in terms of socio-economic characteristics or trip purpose, and it relies on the assumption that if people use a bike from a dock that is within 0.1 mile from a rail station, then they will either use the rail station or use bikeshare as a substitute for transit.

This study contributes to the literature by providing insight on bikeshare behavior during three different time periods in areas of Washington, D.C. that experienced planned transit service disruptions. Transit disruptions are used as an experimental way to observe how bikeshare activity varies if rail transit is no longer an available mode of transportation. Our method accounts for trip-level activity (number of trips between two stations) rather than station-level activity (total number of trips originating from a station). The results provide clear evidence that bikeshare is used as an alternative mode of transportation in times of transit disruptions. This is of significance to policy makers and planners because it indicates that promoting bikeshare systems can be an effective strategy to increase low-carbon mobility.

The remainder of this paper is organized as follows. The next section provides a brief review of the previous literature on transit service disruptions and bikeshare. We then describe the data used in the analysis, followed by an explanation of the two methods used to analyze the data and discussion of the results of our analysis. Finally, the last section provides conclusions, policy implications, and future research directions.

2. Literature review

Planned transit disruptions are increasingly common due to aging infrastructure and the increased need for maintenance. Since summer 2017, transit agencies in New York City, San Francisco, Washington, D.C., Boston, and Baltimore in the United States, and Paris and Madrid in Europe, were among those that closed transit stations or track segments for maintenance purposes (Dicharry, 2017; Guse, 2017; Holland, 2017; Madrid, 2017; MTA, 2017; WMATA, 2017; Campbell, 2018; Phillips, 2018; RATP, 2018). Unlike strikes or special events, planned transit disruptions due to infrastructure maintenance tend to last longer (days to months) and require travelers to use alternative modes of transportation (Zhu and Levinson, 2012).

Transportation disruptions provide opportunities for transport policy change. Responses to such disruptions provide a window into the range of adaptations that are possible (Zhu and Levinson, 2012; Marsden and Docherty, 2013). With the growing urgency for a shift to a low-carbon economy, researchers identify the need for rapid changes to transport policy and travel patterns. Disruptive events make the assumptions around which travel patterns are based more visible. Transport policy changes are characterized as very slow and incremental, in part because of habits in travel behavior (Marsden and Docherty, 2013). However, disruptive events provide evidence that travelers can easily adapt to abrupt changes and that radical policy changes are possible, if not encouraged.

Bikeshare programs have become considerably popular in cities all around the world and allow users to access bicycles on an as-needed basis. They offer a wide range of benefits, including a reduction in emissions and fuel use, increased physical activity, individual financial savings, and support for multimodal transport connections (Shaheen et al., 2010). As of 2016, over 1000 cities worldwide had bikesharing programs in place; this trend continues to increase as more cities consider such systems (Godavarthy and Rahim Taleqani, 2017; Biehl et al., 2018; Nasri et al., 2018). Bikeshare can impact public transit systems by servicing as efficient first- and last-mile connections or as competitors (Shaheen, 2016), and therefore are considered a viable alternative in the event of transit disruptions (especially planned system closures).

Despite the potential of bikeshare systems as an alternative travel mode in cases of transit service disruptions, most research on transit disruptions effects has focused on their impact on highway congestion or modal switches to motorized vehicles (Blumstein and Miller, 1983; Lo and Hall, 2006) and neglected the changes in bikeshare ridership (if available). A few studies have investigated the impact of planned transit closures due to infrastructure maintenance on mode choice, using stated and revealed preference panel surveys (Pnevmatikou et al., 2015; Zhu et al., 2017). Pnevmatikou et al. (2015) did not consider biking as a mode due to low ridership in their area of study (Athens, Greece).

Zhu et al. (2017) studied the same transit disruption as in this paper but focused on behavioral reactions to transit services changes (modal switch, trip cancellation, changing departure time), and collected trip purpose information and socio-economic variables. They focused on the first two surges that occurred (Surges 1 and 2), while this paper focuses on surges that involve system closures and had Capital Bikeshare available as an alternative mode (Surges 2, 4, and 10). Therefore, there was an interesting overlap for Surge 2. They found that most affected surveyed travelers were commuters (82%), were frequent Metro users (75% used Metro at least 5 days a week), mostly male (61%), and had a bachelor's degree or higher (72%). Forty percent of the sampled population indicated that they planned to switch modes during the surge. No strong conclusion was made with respect to biking because the survey did not differentiate between walking and biking, likely because non-motorized transportation in Washington, D.C. makes up a small portion of mode share.

To the best of the authors' knowledge, to date, there are only three other studies that examine the impact of public transit disruption on bikeshare (Fuller et al., 2012; Kaviti et al., 2018; Saberi et al., 2018). The first two studies investigate the impact of separate London Transit strikes on bikeshare use. Fuller et al. (2012) found that the disruption resulted in a statistically significant increase in total number of bicycle trips per day. Similarly, Saberi et al. (2018) found that bikeshare ridership increases during a time of disruption by up to 88%. The latter study was published after the initial submission of this paper and analyzes how the introduction of Single Trip Fare (STF) and transit disruptions impacted bikeshare ridership and revenue in Washington, D.C. using very different approaches than in this present study.

Our study differs from Fuller et al. (2012) and Saberi et al. (2018) in that we explore the effects of three different planned public transit disruptions that lasted 7 to 25 days rather than a single day, and that took place during various seasons in 2016 and 2017. Moreover, the nature of the disruptions differs in that the strike impacted the entire London Tube while the maintenance impacted only segments of Washington, D.C.'s Metro. We do not expect network-wide changes in bikeshare ridership due to the disruptions, but rather spatially local changes near the affected Metro areas. Kaviti et al. (2018) analyzed the impact of pricing and transit disruptions on SafeTrack Surges 1 through 9 using a paired *t*-test simple linear regression and ridership. They did not differentiate between closed stations and single tracking disruptions. They found that the introduction of the Single Trip Fare (STF) positively impacted bikeshare trips. However, they did not control for the presence of surges in their regression model. They separately analyzed the effect of the surges on ridership using week long periods before, during and after each surge and controlled for adverse weather events by removing observations that experienced precipitation and by considering weekdays only (Kaviti et al., 2018).

3. Data

This study utilizes historic bikeshare ridership data available publicly in the study area, which includes information such as date and time of trip, trip duration, trip start/end locations, and membership status of the user for all bikeshare trips (see Fig. 2a). This data was accessed and downloaded from the Capital Bikeshare website for various time periods before, during, and after each SafeTrack project period. This source is comprehensive, but it does not provide any information about station capacity restraints, sociodemographic information about the users of the bikes, or information on trip purpose. We rely on the assumption that trips to rail stations are associated with Metro ridership (either replacing Metro trips or complementing for closures).

We focus on three areas during three different periods. Surge 2 occurred in June 2016 and lasted 16 days (Table 1). It took place in a mostly residential area in southeast Washington, D.C., close to the U.S. Capitol. Stadium Armory and Potomac Avenue stations were completely closed and the nearest open station going into the city center was Eastern Market. Surge 4 occurred in July 2016 and lasted 7 days. Crystal City Metro station was completely shut down and the nearest station going towards the city center was Pentagon City Metro station. It took place in a mixed-use neighborhood of Northern Virginia in the Pentagon area. Surge 10 occurred in November 2016 and lasted 25 days. Brookland CUA and Rhode Island Metro stations were completely closed and the nearest opened station going towards downtown Washington, D.C. was the New York Avenue (NoMa) station. Transfer point Fort Totten station was the nearest opened station to the north of Brookland-CUA Metro station (Fig. 1). Surge 10 spanned several mixed-use areas of Washington, D.C., from the busy Union Station at the south to a relatively residential area at the north.

The time series analysis uses locally specific data for the entire time period. All trips with origins and destinations within 0.5 mile of each affected station are aggregated to daily level. Daily trips are further broken down by the percentage of casual and registered users and by the percentage of morning peak, mid-day, evening peak and night trips. The three dependent variables are the daily bikeshare activity for transit stations within 0.5 mile of affected transit stations for Surges 2, 4, and 10. Weather variables used as controls are obtained from the National Oceanic and Atmospheric Administration (NOAA, 2018). The kernel density estimation analysis uses the entire spatial extent of bikeshare usage and temporally specific periods before, during and after each surge. The data are aggregated to origin-destination to capture directionality in trips. Seasonality is assumed to be constant spatially. Weekends are excluded from the kernel density estimation because bikeshare usage varies considerably spatially, as is shown in the results of the forthcoming time series analysis and complemented by the survey results of Zhu et al. (2017). The methodology is outlined in the following section.

4. Methodology

The main research objectives in this analysis are (1) to measure and quantify the impact of transit disruptions on local bikeshare and (2) to detect where the greatest changes in ridership occur spatially. We use an autoregressive Poisson log-level time series model to address the first question and kernel density estimation (KDE) to address the second. The two methods constitute of comparisons between temporal and spatial scales (surge-specific and network-wide).

4.1. Local trip-level time series analysis

A time series analysis is conducted to assess the statistical and policy significance of disruptions on bikesharing trips at the local scale. The dependent variable is daily trip count between bikeshare stations within 0.5 mi of affected areas from January 1st, 2015 to December 31st, 2017. The ordinary linear model is not appropriate with this data because the response variable assumes discrete values (Fokianos, 2012). The autocorrelation function indicates that time dependency in trips indeed exists (see supplemental material for plots of autocorrelation functions in dependent variables). Daily bikeshare trips, as is often the case with count series data, are not normally distributed and is assumed to follow a Poisson distribution. Based on the nature of the problem and the characteristics of the data, the most suitable model is an autoregressive Poisson model for count time series specified by Liboschik et al. (2017). The conditional mean of the model is linked to its past values and past observations and to potential covariates effects and its conditional distribution is Poisson (Fokianos and Tjostheim, 2011; Fokianos, 2012; Liboschik et al., 2017). The model is specified as log-level. We use three autoregressive terms: 1-day lag, 1-week lag, and 1-year lag to capture both short-term and long-term effects. Seasonal fluctuations are controlled for using weather related variables suggested by Gebhart and Noland (2014). Moreover, we control for non-work day fluctuations using dummy variables (Noland et al., 2016). The last predictor is the intervention variable indicating the presence of the surge.

We are further interested in understanding the nature of each increase. A simple linear regression is used to analyze changes in proportion of casual users and in peak hour usage during each surge (controlling for non-work days and weather variables). A log-level Poisson model is used to analyze changes in trip ridership for weekend and weekday separately. This analysis is done for all trips within 0.5 mi of each surge, similarly to the main time series analysis.

4.2. Spatio-temporal comparison using kernel density estimation

The purpose of this analysis is to visualize changes in ridership due to a planned long-term transit disruption. The main questions asked are where did the greatest concentration of trip increases occur and what is their extent. Kernel density estimation is conducted to detect unusual or atypical increases in bike usage during the surge period. Unusual bike usage refers to trips that are unexpected if there were no surge period. KDE is a non-parametric way to estimate the probability density function of a random variable. KDE is commonly used in transportation research to estimate activity space of individuals (Schönfelder and Axhausen, 2003; Zhang and Krause, 2013) and to estimate probability density of vehicle crash (Anderson, 2009; Xie and Yan, 2013; Ulak et al., 2017). Peer-reviewed studies that apply KDE methods using bikeshare data are limited. Chen et al. (2015) used Washington, D.C. bikeshare data from 2012 to 2014 to identify urban activity centers using KDE. In their study, they use station-level activity (number of bikes leaving and arriving to a particular station during a particular time period) and found that such bikeshare data can successfully identify urban activity centers (Chen et al., 2015).

Unlike previous studies, we use origin-destination level activity instead of station-level activity. The number of origin-destination trip combinations taken during a particular period was calculated. Capital Bikeshare has 440 stations, so the total number of origin destination combinations would be 440^2. This is of course much higher than what is observed in reality, which is closer to about 10–20% of those trip combinations. Each trip combination has an attribute (trip count) that designates the number of times a trip was taken for a particular time period.

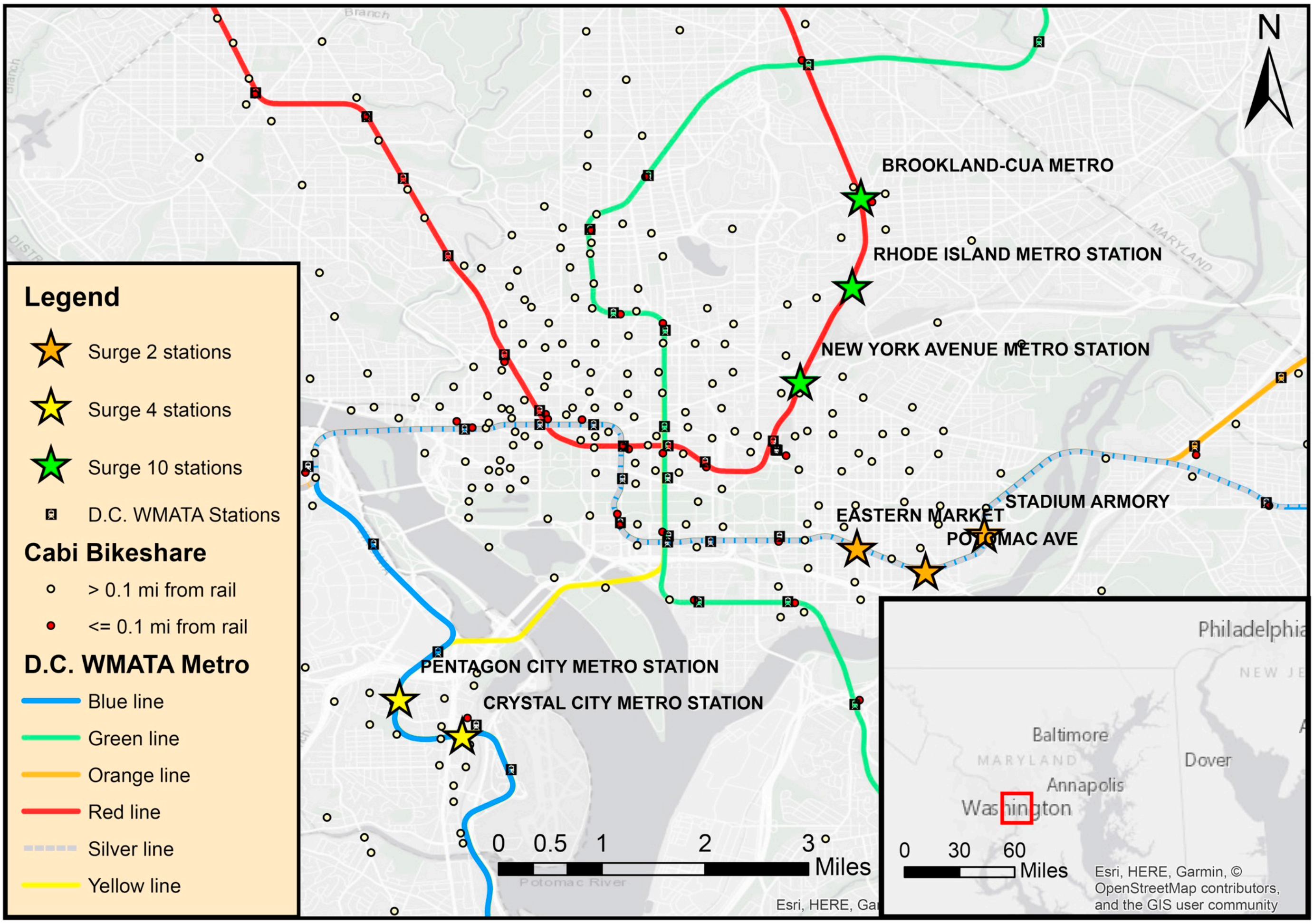

Fig. 1. Map of study area.

Trip ID	Time	Start Station ID	End Station ID	Rider Type
1	1/1/2016 8:35	29	78	Casual
2	1/1/2016 11:20	100	21	Member
3	1/2/2016 6:02	29	78	Member
4	1/2/2016 12:27	100	19	Member
5	1/3/2016 1:45	100	19	Casual

Date	Trip Count (Subset: Trip pairs within 0.5 mi of Surge X)	% Casual Riders	% Peak hour riders
1/1/16	2	50%	50%
1/2/16	2	0%	50%
1/3/16	1	100%	0%
1/4/16	...	...	...

Station Pair	Trip Count (Subset: 1/1-1/2/2016)
29-78	2
100-21	1
100-19	1

Fig. 2. Description of bikeshare data structure. (a) Raw trip level data: each individual trip has its own row. Data contains information on trip duration, time and date, membership type, bike number, etc. (b) Time-series data: each date has its own row and trip count is aggregated. Some information is preserved by introducing percentages of membership type and time of usage and mean duration of trip. In this study, we subset trips within a certain radius of each surge. (c) Origin-destination or station pair level data: each station pair has its own row and a new column is created with the number of trips taken per pair. In this study, we subset trips within a certain time frame. Unlike station level data, directionality of trip is preserved.

While KDE works on both point (e.g., stations) and polyline (trips in Fig. 2c) data, we chose not to aggregate the data to station level for the following two reasons. First, the surges were local to a few transit stations in a network of 91 rail stations. Second, the nature of the transit disruption is such that it impacted people living along linear track segments (one or more stations in a row). Therefore, we expect trips from the same station to decrease in one direction and to increase in another. To capture the direction and magnitude of trips, one must use origin-destination data, as all this information would be lost in station-level data. For each surge, the change in number of trips for three time periods was calculated: the days preceding the surge, the same time period one year earlier (2015), and the same time period one year later (2017).

KDE on its own estimates the probability density of station-pair combinations that increased during a surge. Each trip combination is assigned a weight based on how much ridership increased during the surge. This weight is simply defined as the squared change in ridership. We squared the change in ridership in order to emphasize significant increases in activity. The limitation with such a measure is that trips that increased from 20 to 40 were weighted less strongly than popular trips that increased from 200 to 250. Nonetheless, this method was useful in capturing increases in bikeshare ridership close to each surge area, as outlined in the results.

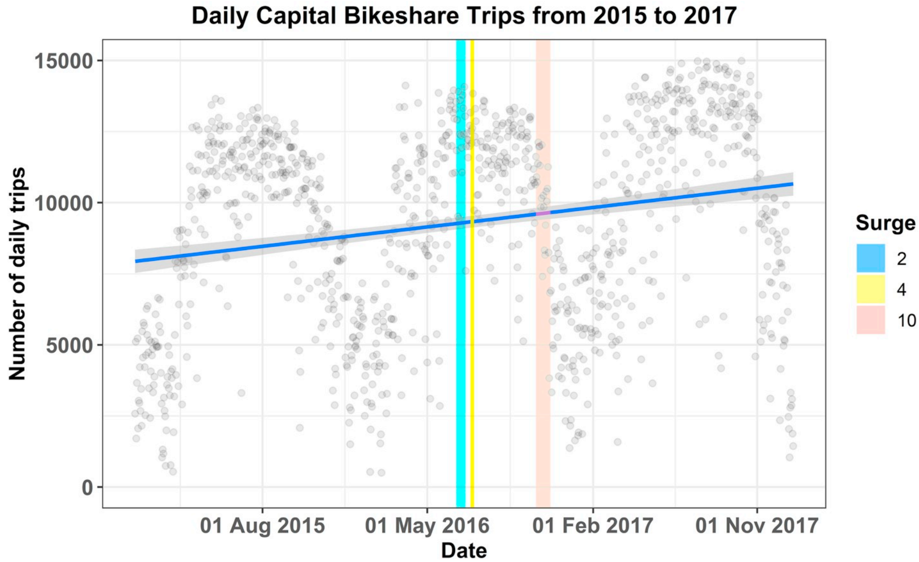

Fig. 3. Daily number of trips from January 2015 to December 2017. Notice the prominent seasonal fluctuations and the growing trend in the three-year period in Washington D.C.

5. Analysis and results

Washington, D.C.'s Capital Bikeshare trips increased on average 9% annually from 2015 to 2017 (Fig. 3). Table 2 outlines daily average number of trips for all capital bikeshare trips and for bikeshare trips within 0.5 mi of each surge one year before, one week before, during, one week after, and one year after each surge. We use average number of daily trips because of differences in surge lengths (varying from 5 weekdays to 15 weekdays). Weekend trips are excluded from this table because of their varying spatial dynamics. All trips, local and network-wide, increased from 2015 to 2017. The average number of trips during the surge is shows a clear increase during the surge for activity within 0.5 mi of each surge but not for the entire bikeshare network. Average number of trips shortly before and after each surge remain relatively constant, hinting that the surges did not have a lasting impact on bikeshare ridership. Fig. 4 displays a visual of non-adjusted daily trips for the times shortly before and after each surge. One can observe that trips appear to return to original numbers after transit disruptions end.

5.1. Local trip-level time series analysis

We capture the effect of each surge by detrending and de-seasonalizing locally specific data using a regression. Temperature, maximum wind speed, and visibility were used to control for seasonality. Precipitation was excluded from this analysis because of its very low correlation with daily bikeshare trips. Dummy variables are used to control for non-workdays (weekends and holidays) and non-school days (mid-June to end of August). A dummy variable indicating the presence of each surge is used as the intervention variable.

The results of the Poisson model and autoregressive Poisson model for each surge are presented in Table 3. We find that the Poisson model with autoregressive terms performs better than the traditional Poisson model for each of the surges when using the AIC and log-likelihood coefficients. Moreover, the autoregressive Poisson model does better at reducing autocorrelation in the residuals (refer to supplementary material for autocorrelation function plots of model residuals). The time lags are all significant, confirming the dependent nature of bikeshare data on past observations. Temperature and visibility have a positive and significant effect and windspeed has a negative and significant effect on bikesharing trips. These weather effects are in line with the literature (Corcoran et al., 2014; Gebhart and Noland, 2014; Noland et al., 2016). Non-working days have locally specific impacts. For Surges 4 (Pentagon area) and 10 (downtown Washington, D.C.), weekends and holidays see fewer activity. Surge 2, which took place in a more residential sector of the District of Columbia, actually sees an increase in trips during weekends and holidays. Since non-working days have spatially different impacts on the region, they are excluded from the KDE analysis, which requires variables to be spatially constant. The summer dummy variable, which accounts for non-school days, negatively impacts bikeshare activity in the surge areas. None of the areas are strong tourist attractions so these results make sense. Controlling for the introduction of the Single Trip Fare (STF) in June 2016 does not

Table 2
Description of bikeshare activity for Surges 2, 4 & 10.

	Surge 2		Surge 4		Surge 10	
Pre-Surge Time period (Weekdays)	6/2–6/17/2016		7/5–7/11/2016		10/6–10/28/2016	
Surge Time Period	6/18–7/4/2016		7/12–7/18/2016		10/29–11/22/2016	
Post-Surge Time period (Weekdays)	7/5–7/18/2016		7/19–7/25/2016		11/23–12/15/2016	
Total Length of Surge in days	16		7		25	
Length of Surge in Weekdays	10		5		15	
	Stations within 0.5 mi	All Stations	Stations within 0.5 mi	All Stations	Stations within 0.5 mi	All Stations
Total Number of Weekday Trips during Surge	758	118,572	892	60,116	1303	151,812
Average number of weekday trips 1 year before Surge	58.6	11,454	131	11,957	47.4	9187
Average number of weekday trips before Surge	44.8	12,407	126	12,185	59.9	11,648
Average number of weekday trips during Surge	75.8	11,857	178	12,023	86.9	10,121
Average number of weekday trips after Surge	49.3	12,104	129	12,173	43	7058
Average number of weekday trips one year after Surge	60.2	13,708	149	12,376	51.2	9687

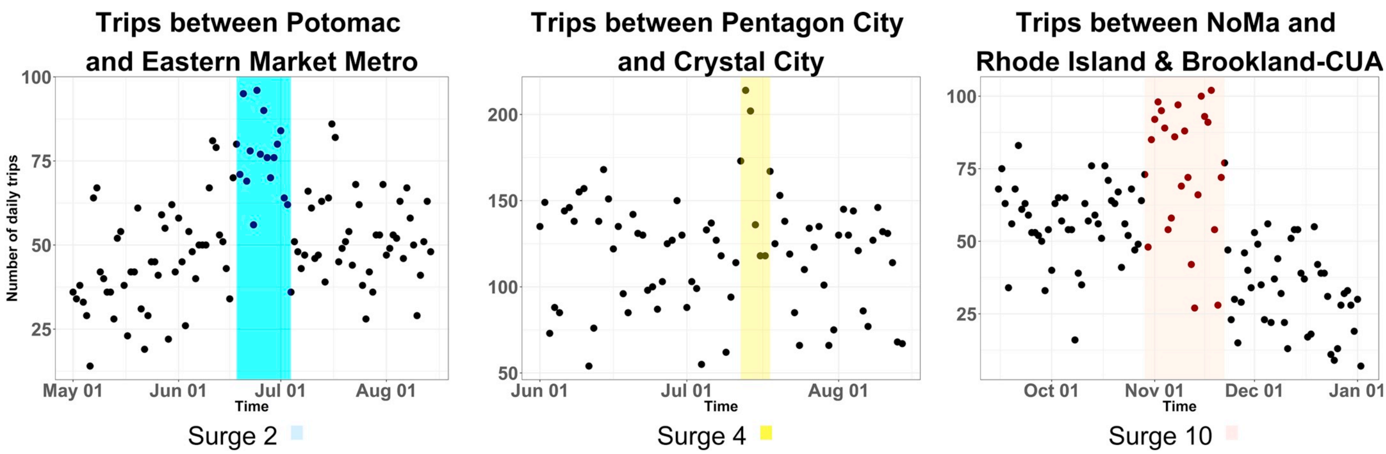

Fig. 4. Non-adjusted weekday ridership between bikeshare stations within 0.50 mi of disrupted Metro stations before, during (as shaded), and after Surges 2, 4 & 10 in 2016.

significantly improve the model for any of the surges and is therefore excluded from the final models. Finally, the intervention variable, which is specified by the dates in Table 1, is statistically significant and positive for all three respective surges. We now look at the practical significance of the results.

The models are specified as log-level and the coefficients β in Table 3 for the Poisson Autoregressive model are converted to percentages in Table 4 using the following formula:

$$\%\Delta y = 100 * (e^{\beta} - 1)$$

For a one-unit change in independent variable x, we expect y to change by the exponent of the coefficient of x minus one multiplied by 100%. The transit disruptions (presence of surge) lead to between 24 and 45% more trips in bikeshare stations within 0.5 mile of each surge. This amounts to about 11, 22 and 21 additional daily trips around Surges 2, 4, and 10, respectively, compared to average daily ridership during the three-year span. While this may not appear substantial, one must consider that bikeshare activity is dependent on bikeshare station capacity (Faghih-Imani et al., 2017). Given that the transit stations often have one bikeshare station with 15–20 racks, some of which should always remain empty so that people can return bikes easily, the magnitude of bikeshare trips is limited by this important factor. We estimate that a combined 856 additional trips were taken between stations within 0.5 mile of each affected area. This number is likely to be higher if one accounts for changes in bikeshare activity due to the slowdown of the transit system throughout the region.

While trips significantly increased during the surge, there is interest in understanding the nature such increase. We performed regressions for trips within 0.5 mi of each surge and tested the impact of the disruptions on the proportion of casual users (non-registered users), the proportion of trips taking place during peak hours (which we defined as starting between 6 am and 9 am and 3 pm and 6 pm), and weekend versus weekday only trips. We used a generalized linear regression for the first two proportion variables and a log-linear Poisson model for the latter two count variables and controlled for weather and non-working days (as applicable). Proportion of casual users increased around Surges 2 and 10, indicating a possibility of increased ridership from new groups. Surges 2 and 10 spanned two weeks or longer, perhaps giving more possibility for increases in casual ridership than Surge 4, which lasted only one week. Surge 10 was associated with statistically significant increases in the proportion of peak hour users; however, no conclusion can be drawn with respect to the other two surges. Weekend activity increased, albeit to a lesser extent than weekday activity for Surge 10 and did not statistically significantly increase in the Surge 2

Table 4
Interpretation of coefficients as percentage of change in y for a one-unit change in x.

	Surge 2	Surge 4	Surge 10
Presence of surge	24.21%	24.18%	45.14%
Temperature	1.05%	1.17%	0.96%
Wind speed	−0.77%	−0.64%	−0.79%
Visibility	9.89%	12.70%	12.0%
Weekends/Holidays	16.29%	−37.71%	−18.48%
Summer	−5.32%	−6.46%	−7.41%

Table 3
Results of time series analysis for Surges 2, 4 and 10.

	Poisson			Poisson with Autoregressive terms		
Coefficients (β)	Surge 2	Surge 4	Surge 10	Surge 2	Surge 4	Surge 10
Intercept	1.898 *** (0.06)	2.397 *** (0.04)	1.797 *** (0.06)	1.18 *** (0.07)	1.52 *** (0.05)	1.05 ***(0.07)
1-day lag	N/A	N/A	N/A	0.21 *** (0.014)	0.20 *** (0.008)	0.21 *** (0.01)
1-week lag	N/A	N/A	N/A	0.098 *** (0.012)	0.087 *** (0.008)	0.092 *** (0.01)
1-year lag	N/A	N/A	N/A	−0.010 *** (0.004)	0.009*** (0.003)	0.04 *** (0.004)
Presence of Surge	0.302 *** (0.03)	0.258 *** (0.03)	0.573 *** (0.024)	0.22 *** (0.03)	0.217 *** (0.03)	0.372 *** (0.025)
Temperature	0.016 *** (0.0003)	0.017 *** (0.0002)	0.015 *** (0.0003)	0.010 *** (0.0004)	0.013 *** (0.0003)	0.0096 *** (0.0004)
Wind Speed	−0.009 *** (0.0009)	−0.008 *** (0.0007)	−0.009 *** (0.0009)	−0.008 *** (0.0009)	−0.006 *** (0.0007)	−0.008 *** (0.0009)
Visibility	0.107 *** (0.006)	0.14 *** (0.004)	0.14 *** (0.006)	0.094 *** (0.006)	0.119 *** (0.004)	0.113 *** (0.006)
Weekends/Holidays	0.194 *** (0.009)	−0.58 *** (0.008)	−0.26 *** (0.010)	0.15 *** (0.010)	−0.473 *** (0.010)	−0.204 *** (0.011)
Summer	−0.076 *** (0.013)	−0.094 *** (0.009)	−0.115 *** (0.013)	−0.055 *** (0.013)	−0.067 *** (0.009)	−0.077 *** (0.013)
AIC	9945	14,066	10,324	9572.5	13,459	9682
Log Likelihood	−4965	−7026	−5155	−4776	−6719	−4831

(***) indicates significance at 0.01 level.

Table 5
Impact (β) of presence of surge on selected variables.

Dependent variable	Surge 2 (16 days)	Surge 4 (7 days)	Surge 10 (25 days)
% of casual users	0.06 (p = 0.0002) ***	0.06 (p = 0.12)	0.11 (p < 0.0001) ***
% of peak hour users	0.04 (p = 0.14)	−0.01 (p = 0.76)	0.10 (p < 0.0001) ***
Weekend only (log)	0.16 (p = 0.84)	0.24 (p = 0.0002) ***	0.38 (p < 0.0001) ***
Weekday only (log)	0.42 (p < 0.0001) ***	0.26 (p < 0.0001) ***	0.62 (p < 0.0001) ***

(***) indicates significance at 0.01 level. N = 1096 for first two variables; N = 314 for Weekend only; N = 782 for Weekday only.

area. Weekend activity for Surge 4 is significant but one should note that only one weekend occurred in that period. Finally, weekday trips mirror the results of the Poisson model in Table 3, with slightly larger coefficients, indicating that the greatest growth came from weekday trips across all surges (Table 5).

5.2. Kernel density estimation

Kernel density estimation is used in this paper estimate the spatial distribution of increases in trip ridership. In our case, we use 10, 5, and 15 weekdays for Surges 2, 4, and 10, respectively, and compare with the same time duration before the surge (pre-surge), and one year before and after the surge (full results available in the Supplementary Material). Results from the time series analysis indicate that trips within 0.50 mi of each surge increased significantly. Without applying KDE, it is still unclear how the increases in trips nearest to the surge compare to other increases in the rest of the network. Surge 2, for example, happened at a time when tourist activity increases and saw a large increase in trips around the National Mall, a popular tourist attraction. To minimize single period temporal effects, we use Raster Cell Statistics in ArcGIS to sum the combined kernel density estimates of all time periods and consistently find that the surge areas display the highest increases in trips, exceeding visually the densities of tourism increases (Fig. 5).

The highest distribution of increases in trips occurs nearest to the first opened stations in the direction of the downtown city center (New York Ave, Eastern Market and Pentagon City) and disperses in the direction of the closed transit stations. Because of this directionality, it appears that travelers close to the disruptions temporarily used bikeshare as a way to reach unaffected nearby transit stations rather than as a substitute for a full transit trip. Future research is suggested to formally test this asymmetric flow. Transit closures impacted the rest of the network by slowing down service and leading to overcrowding on unimpacted transit lines. However, based on this analysis, the effects of the surge on bikeshare activity beyond the 0.5 mi radius are not evident. We observe moderate increases in trips in the city center for all surges. Yet, we refrain from attributing network wide changes in bikeshare ridership to the surges due to the spatially and temporally variant nature of the network-wide data.

An important takeaway is that stations in close proximity of Surges 2, 4, and 10 all display atypical increases in bikeshare ridership. The changes are not only atypical, they are the greatest changes in bikeshare ridership out of the entire network, exceeding ridership changes from weekday touristic activity. The surges have a considerable impact on bikeshare ridership trip pairs, more so than what is seen with total station activity. This is important to consider because the origin-destination data (station pairs) that provide direction and magnitude of trips (in length) were found to be non-trivial factors in this analysis.

6. Conclusion

This study sought to explore the effects of three public transit disruptions in Washington, D.C. during the SafeTrack project on bikeshare demand. The SafeTrack project took place from June 2016 to June 2017 through 16 different surges. Initial testing suggested that the slowdown caused by single tracking surges did not meaningfully impact trips within 0.5 mi of affected areas and thus were excluded from the main analysis. Surges 2, 4, and 10 qualified for this analysis as they consisted of the track closure that affected two or more stations, had bikeshare available within a reasonable distance of each affected Metro station, and had acceptable first- and last-mile biking distances between rail stations.

Our analysis overall suggests that the transit station closures had a considerable effect on bikeshare ridership. The increase in bikeshare traffic between closed and opened rail stations and the results of the KDE visualization indicate that it is likely that bikeshare was used as first- and last-mile solutions rather than as a substitute for transit. This is an important finding as it furthers understanding of interactions between modes during transit disruptions. Surges that required bike users to bike distances longer than 2.5 miles did not see considerable increases in ridership. At that point, travelers likely reverted to motorized modes such as bus or private car. Weekday ridership increased more than weekend ridership, which indicates a possibility of commuters rather than leisure trips. Registered users make up on average around 80–90% of all bikeshare users in Washington, D.C., but there was an interest in understanding whether the proportion of casual users increased during the surge. While increases in proportion of casual users were significant for Surges 2 and 10, one should be careful in interpreting these results as surges may have attracted new riders who became registered users because of the surge and thus would not be captured in the casual user proportion. More analysis is needed to understand the nature of increases in bikeshare ridership during transit disruptions. A time-of-day and day-of-week analysis showed that most of the increase in ridership occurred during weekdays for all surges while peak hour usage increased significantly for Surge 10 but not for the others. These differences between surges are not surprising given that Surge 10 lasted nearly one month and spanned a busier and wider area of Washington D.C. than the other surges. Bikeshare ridership in the affected areas appeared to return their pre-surge stage after each surge, suggesting that the disruptions did not have a lasting effect on bikeshare ridership.

Conclusively, transit disruptions provide a unique opportunity to understand alternatives for transit riders and how travel decisions are made, both of which are crucial for drafting future transportation policies (Zhu and Levinson, 2012). Promoting bikeshare can be used as a strategy to increase or promote low-carbon mobility in Washington, D.C. Policy and planning recommendations for bikeshare management are to (1) consider bikeshare station capacity during a transit disruption. Station capacity is much lower than the number of people who have to switch modes because of transit disruptions. Because bikeshare activity is limited by station capacity, planners should consider this when providing alternative modes for transit riders; (2) account for proximity of rail and bikeshare stations - several surges did not qualify for this study because bikeshare was further than 0.25 mile from a station and we considered that to be too far to be a viable alternative to transit; and (3) examine rail station spacing - some stations had bikeshare available at both stations, but the rail spacing exceeded 3 miles. This is more complicated because rail transit spacing is established infrastructure that cannot be cheaply or quickly altered. One recommendation is to provide bikeshare stations between two consecutive rail stations to allow people who live or work between two stations to use bikeshare as a complementing option.

Future research could focus on complementing this type of analysis with surveys to confirm the trip purpose of bikeshare users and understand the attitudinal preferences towards modal shift to bikeshare during transit disruptions, as well as its underlying reasons. This would

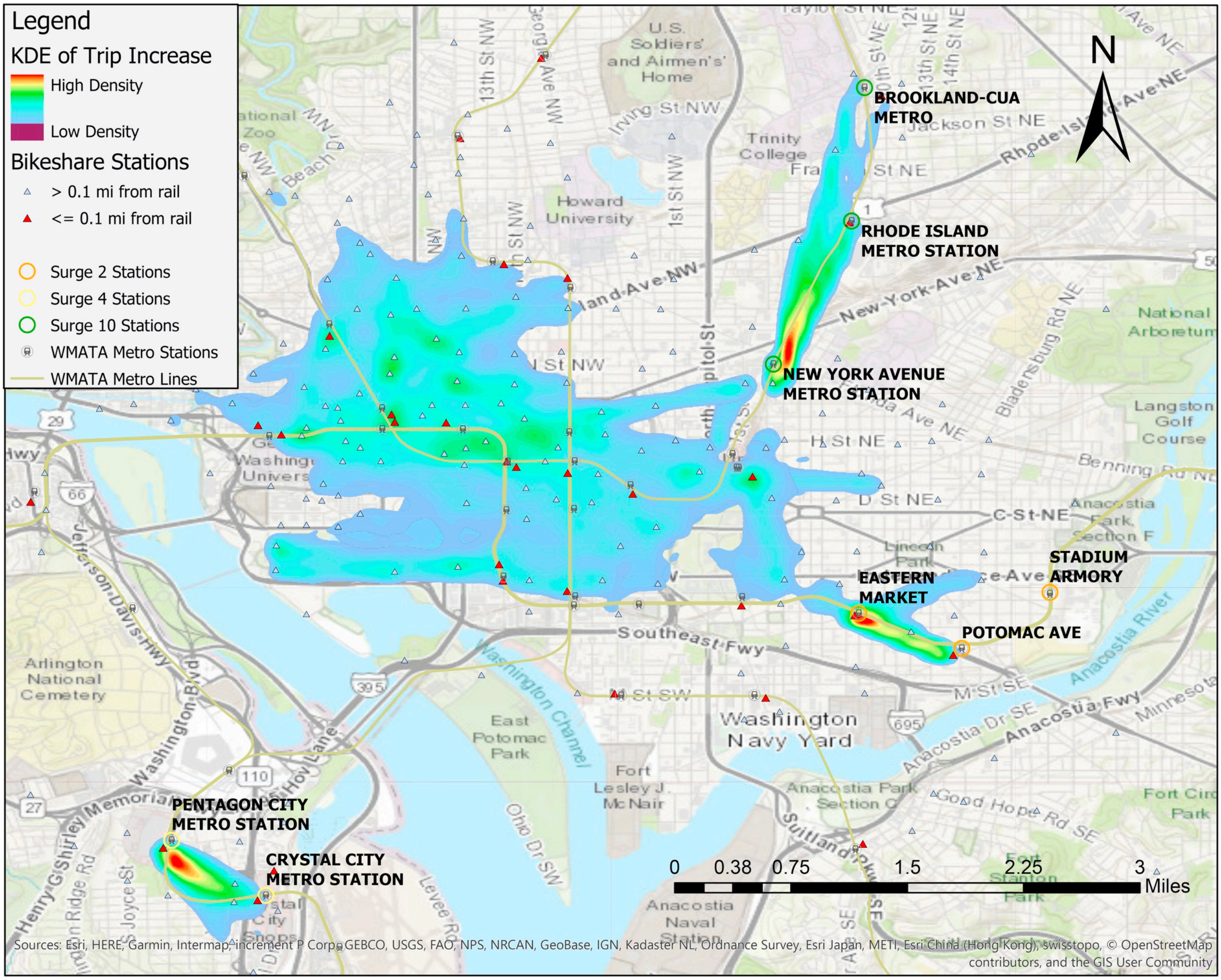

Fig. 5. KDE visualization of ridership increases during surge time periods (combined for Surges 2, 4, and 10) when compared to pre-surge time 2016, same time period in 2015, and same time period in 2017. Estimates in the bottom quintile are excluded in order to visualize the top 80% of increases in trips estimates.

help planners and policy makers expand and improve bikeshare systems in large metropolitan areas and to promote bikeshare ridership as it provides information on whether planned transit disruption attracts new bikeshare users. It would also be interesting to apply this type of analysis to other cities possessing bikeshare that have experienced or are planning for a planned transit disruption in the future, to better understand how travelers respond.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jtrangeo.2019.03.004.

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