TRAVEL BEHAVIOR REACTIONS TO TRANSIT SERVICES DISRUPTIONS: A CASE STUDY ON THE WASHINGTON D.C. METRO SAFETRACK PROJECT

by

Hamza Masud
A Thesis
Submitted to the
Graduate Faculty
of
George Mason University
in Partial Fulfillment of
The Requirements for the Degree
of
Master of Science
Civil & Infrastructure Engineering

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DEDICATION

This is dedicated to my loving wife Namra Qureshi, my parents, and the Holy Prophet (PBUH).

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LIST OF ABBREVIATIONS

Washington Metropolitan Area Transit Authority..WMATA
Continuous Single Track..CST
Line Segment Shutdown..LSS
District of Columbia...D.C

ABSTRACT

TRAVEL BEHAVIOR REACTIONS TO TRANSIT SERVICES DISRUPTIONS: A CASE STUDY ON THE WASHINGTON D.C. METRO SAFETRACK PROJECT

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George Mason University, 2019

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Major transit infrastructure disruptions have become more frequent due to increasing maintenance needs for an aging infrastructure, system failures, and disasters. Understanding travel behavior reactions to service disruptions based on empirical observations is a fundamental step toward planning and operating an efficient and reliable transportation system. Few studies in the literature investigated the behavioral and system impact of transit service disruptions. To bridge this gap in literature, this research investigated travel behavioral reactions to transit service disruptions during the Washington D.C. Metro SafeTrack projects using a unique panel survey. This study will offer new insights on multi-modal, multi-dimensional travel behavioral responses to major transit network disruptions, a critically theoretical prerequisite toward developing and implementing effective strategies (e.g., how to optimally deploy the reserved bus fleet) that minimize system impact and improve transit system reliability and resiliency.

INTRODUCTION

Major transit infrastructure disruptions have become more frequent due to increasing maintenance needs for an aging infrastructure, system failures, and disasters. Both transportation agencies and travelers need better information to prepare for such events. Understanding travel behavior reactions to service disruptions based on empirical observations is a fundamental step toward planning and operating an efficient and reliable transportation system. However, how individuals respond to major disruptions in transportation networks, caused by major accidents, maintenance, disasters, or targeted attacks is one of the least studied basic research questions in travel behavior (Di et al. 2015; Zhu and Levinson, 2012; Zhu et al. 2010; Zhu et al. 2016; Zhu and Levinson, 2015; Faturechi and Miller-Hooks, 2014; Mendonca and Wallace, 2006; Nie et al. 2012; Yin et al. 2012). Compared to other modes, there are even fewer studies on the behavioral and system impact of transit service disruptions (Zhu and Levinson, 2012). Previous studies employed either stated preference surveys or limited behavior data collected during transit strikes that typically lasted for a very short period of time (Ferguson, 1992; Lo and Hall, 2006; Van Exel and Reitveld, 2001; Blumstein and Miller, 1983; Anderson, 2013; Gordon and Fittante, 1984; Giuliano and Golob, 1998). With transit service disruptions, transit riders suffer significant delays or are forced to adopt other travel options. In the worst case (e.g., Hurricane Katrina), transit service shutdowns during natural disasters led to complete loss of mobility for residents without a personal vehicle, which delayed evacuation and increased loses. Such events illustrate the vulnerability of the transit network and the need to better understand users' responses to transit network disruptions.

In the event of transit service disruptions, affected transit riders may react by adjusting their routes, departure times, travel modes, destinations, and/or cancelling trips. These initial behavioral adjustments will likely cause additional non-transit travelers to alter their travel behavior too, disrupting the existing system equilibrium and creating complex system re-equilibration dynamics through a series of individual learning and adaption processes. Certain transit riders may no longer use transit as the default mode for their trips even after transit service resumes. The emergence of various sharing economy travel options (e.g., vehicle sharing, long-term and dynamic ride sharing, ride-hailing services like Uber Pool/Lyft Line, dynamic/micro-transit without fixed routes or schedules, and bike sharing) offer new ways for travelers to minimize the mobility impact of transit service disruptions. These new possibilities of behavioral reactions to transit services disruptions in a multi-modal transportation network have not been addressed in the literature.

To bridge this gap in the literature, this research investigated travel behavioral reactions to transit service disruptions using a unique panel data collected during the Washington D.C. Metro SafeTrack projects, a series of track work for safety enhancement that leads to significant capacity reduction or service disruptions. These events offer an unprecedented opportunity to observe actually behavior changes during transit services disruptions and how they differ (or not) from their stated preference before the events. This study will offer new insights on multi-modal, multi-dimensional travel behavioral responses to major transit network disruptions, a critically theoretical prerequisite toward developing and implementing effective strategies (e.g., how to optimally deploy the reserved bus fleet) that minimize system impact and improve transit system reliability and resiliency.

Organization of Thesis

This thesis includes two major parts, each of which addresses a specific research gap in the literature related to transit network disruptions. The first part is a description analysis of behavioral reactions to transit network disruptions based on a panel survey conducted during the Washington Metro SafeTrack projects. The related research has been published on Transportation Research Record (Zhu et al. 2017). The second part develops a hierarchical decision tree model on behavioral reactions (doing nothing, changing departure time, changing mode, changing destination, or canceling trips) to major network disruptions. These quantitative analyses complements the qualitative analysis in the first part of this thesis to help agencies and the public to better understand the impact of major network disruptions, and better predict the behavioral adjustments people may adopt to mitigate the impact of such disruptions on their daily lives. Both parts will add much needed empirical evidence in this research area.

LITERATURE REVIEW

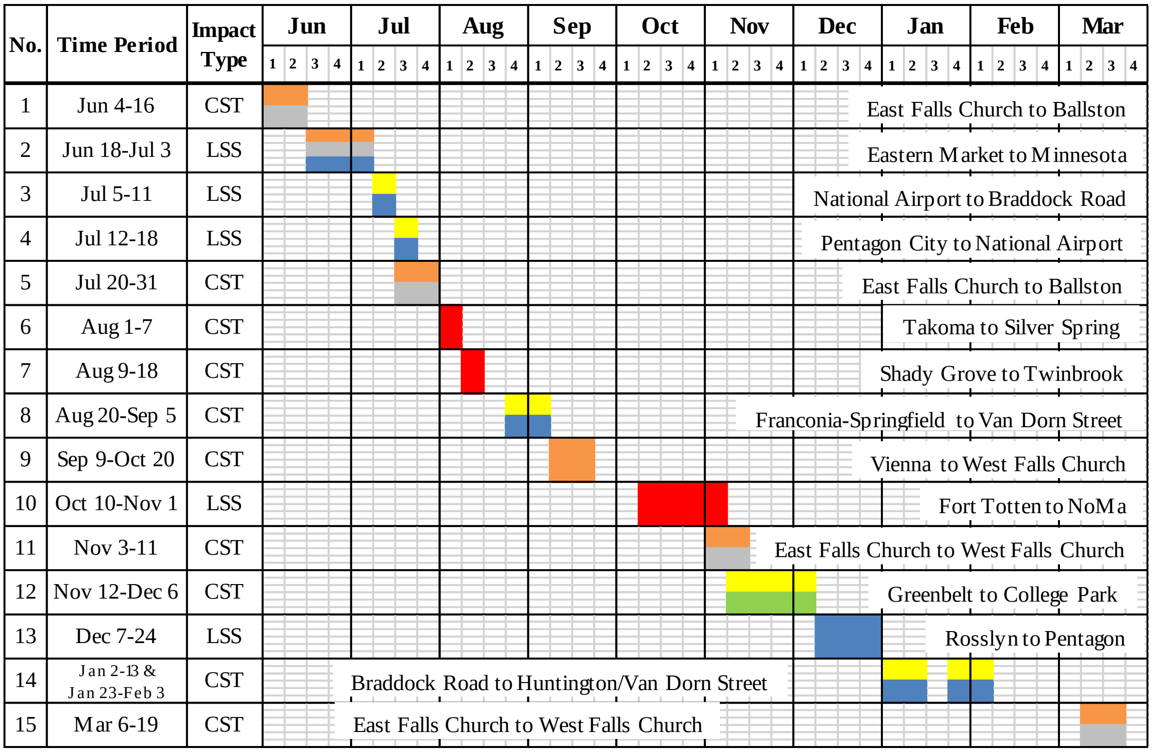
Transit network disruptions are not unusual. They could be the results of accidents, system failure, maintenance needs, and man-made or natural disasters. The impact of each incident varies both in geographic and time dimensions (Zhu et al. 2010). Replacing a breakdown bus may only take half an hour. However, it is much harder to restore a metro service when something goes wrong. For example, a simple runaway event in London created a chaos among travelers early morning on August 13, 2010. A public inquiry was made due to a five-hour breakdown of Urban Transit Rail System, of Singapore, that discommoded thousands of commuters on December 15, 2011. Unlike the surface traffic network, it is almost impossible to reroute metro services (De-Los-Santos et al. 2012). Bridging affected metro stations through a parallel bus service is a widely used practice to maintain the metro service (Kepaptsoglou and Karlaftis, 2009). However, significant delays could be added due to the transfers, and the limited capacity of buses compared to metro trains. These delays could cause repercussion on the entire network as travelers may miss their connections (Jespersen-Groth et al. 2009).

For an extended event, travelers are usually better informed and can adjust their travel behavior accordingly. For example, during the 13-day long transit strikes in New York City in 1967, 10% travelers cancelled trips, 16.7% switched to carpool, and 50% drove alone. In a 1995 transit strike in Netherland, 30% travelers switched to driving and another 10% cancelled trips. Moreover, longer transit service disruptions could also have long-term effects on transit ridership. For example, the 1981 and 1986 Orange County transit strike in California reduced 15% to 20% of transit trips even after the strike (Ferguson, 1992). The New York City transit strike also caused 2.1-2.6% reduction in transit ridership. Zhu and Levinson provided a detailed review on this topic (2012).

However, the aforementioned studies show the significance of transit service disruptions on travel behavior and transportation system performance, several critical research needs remain. Many previous studies rely on stated-preference, which may not capture the true travel behavior. Moreover, no study has investigated the learning and adaption process during the service disruption, which prevents us from modeling the re-equilibration process during such an event. This study will address those issues using a panel data collected both before and after the transit service disruptions.

DATA COLLECTION

Between June 2016 and March 2017, the Washington Metro system will either shuts down or significantly reduces Metro rail transit services (through continuous single track between stations) to accommodate 15 separate SafeTrack system maintenance projects (dubbed as “surge”). This event provides a unique opportunity to improve our knowledge on travelers’ behavior responses to major transit system disruptions and the consequent system mobility, reliability and resiliency impact. Figure 1 summarizes the date, affected metro lines and sections, and maintenance type of each Safetrack surge.



* Continuous Single Track(CST), Line Segment Shutdown(LSS)

** Different colors in the Metro Shutdown Schedule Chart represent the color-coded Metro Lines in DC

Figure 1 Timeline of the 15 Metro SafeTrack Projects and the Metro Lines Affected

Travel surveys were conducted both before and after each surge to collect panel data of reported travel choices among metro riders. Before each surge, survey questionnaires were distributed at metro stations that would be severely affected by the particular SafeTrack project. Respondents may choose to complete the paper-based survey and mail it back to the research team using the pre-paid envelop, or to complete the web-based survey with the same questions by visiting the survey website using a computer, or scanning the QR codes using a smartphone. Questions included the awareness of the metro shutdown event, the characteristics of the current trip, their habit of traffic information acquisition (or lack thereof), the planned changes (or no change) due to the upcoming metro shutdown, and their social demographic information. Respondents were also asked if they would like to complete a follow-up survey after the particular SafeTrack surge and their contact information if they agreed to participate.

A follow-up survey was mailed to the respondents who agreed to complete a follow-up survey. Questions included the travel choices respondents tried during the SafeTrack surge in reaction to the service disruptions, and the most effective choice they eventually chose. Respondents also reported their new travel patterns after the metro service is completed restored.

Surge 01 and 02

This study used the data collected before and after Surge 1 and Surge 2 of the SafeTrack project. Surge 1 led to continuous single-track service on the Orange/Silver line between East Falls Church and Ballston stations (red line in Figure 2) between 06/04/2016 and 06/16/2016. It reduced the capacity of metro Silver and Orange line segments west of Ballston by 70% (rush hour headway goes from 6 minutes to 18 minutes), and the rest of the two lines by about 30%. Surge 2 shut down the Orange/Silver/Blue line segments between Eastern Market and Minnesota Ave & Benning Road stations. It also shut down the Blue line segment between Rosslyn and Arlington Cemetery, and reduced the capacity for the rest of Orange and Silver lines by 40% to 60%. The pre-survey questionnaires were distributed one week before Surge 1 and Surge 2 in the most severely affected stations (yellow in Figure 2) during the weekday daytime (7am-7pm).

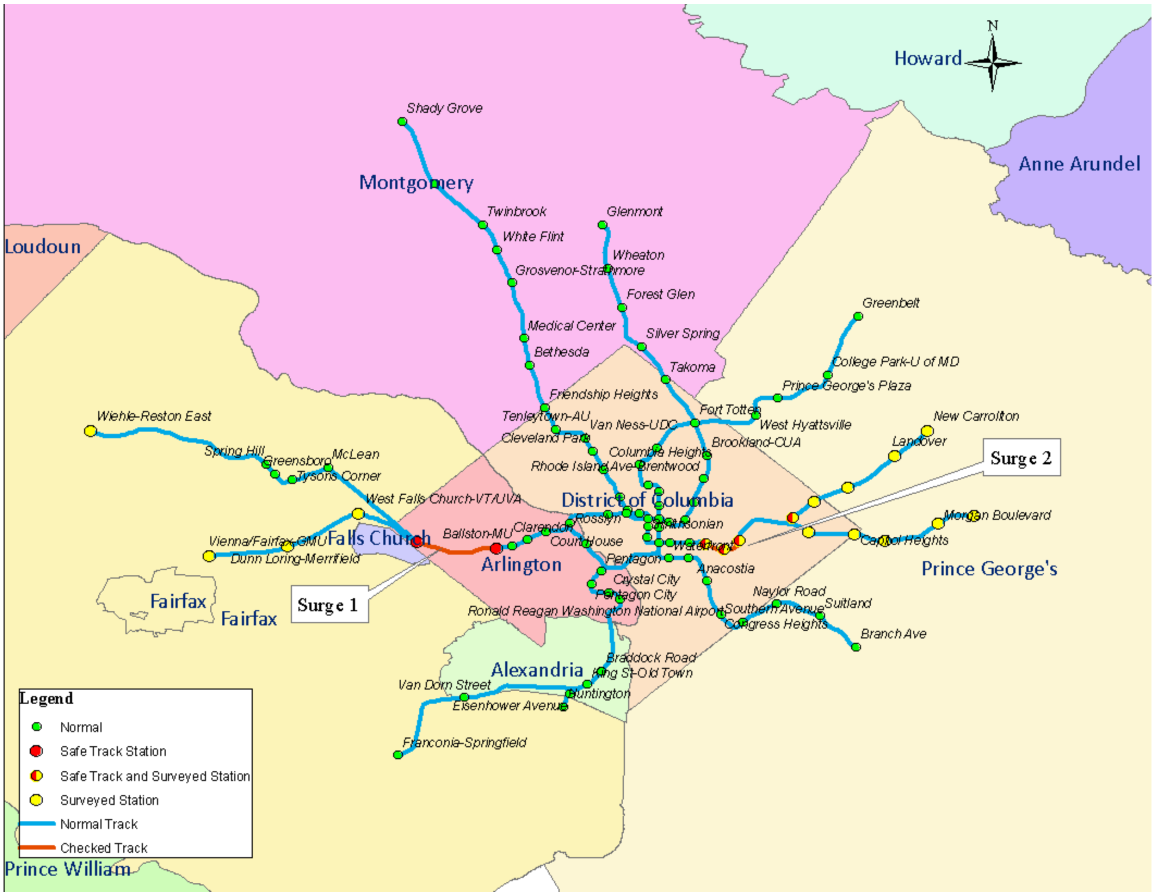


Figure 2 Affected Metro segments and Metro stations where survey questionnaires were distributed during SafeTrack Surge 1 and Surge 2

PRE SURVEY RESULTS

In total 875 and 1179 survey, questionnaires were distributed for Surge 1, and Surge 2, and 318 and 420 responses were received, respectively. This represents a response rate of 36% in both surges, which is very high for a randomly distributed survey. This could be due to the extensive media coverage and high profile public debate surrounding this event.

Table 1 summarizes the social demographic information of survey respondents. About 80% of the pre-survey respondents chose to fill in the paper-based survey and mail it back to the research team, while about 20% of them scanned the QR codes using their smartphones and answered the questionnaire online. About 54% of surge 1 respondents were female, but female only represented 37% of all respondents during surge 2. The majority of survey respondents are between the age 25 and 64, and the group of 45-54 was the highest in both surge 1 and surge 2. Most of the survey respondents hold either a Bachelor's degree, or a Graduate degree in Surge 1, and the household incomes are in the range of \$75,000 and \$200,000. This is consistent with an early poll conducted by the Washington Post, which showed that 66% of Orange Line riders were college graduates, and 60% had an annual income of more than \$100,000 (Zhu et al. 2017). This is also because the affected stations in Surge 1 are located in the affluent Northern Virginia area. In contrast, more respondents reported lower education level and income in Surge 2, which went through a less wealthy neighborhood in D.C. and the Prince George's County in Maryland.

Table 1 Demographics of Survey Respondents during Metro SafeTrack Surge 1 and Surge 2

Pre Survey		
	Surge 1	Surge 2
Type		
Hand Filled	77.04%	80.00%
QR Code	22.96%	20.00%
Gender		
Male	45.60%	61.67%
Female	54.40%	36.67%
Age Range		
Under 15	0.00%	0.24%
16-18	0.31%	0.48%
19-24	5.97%	1.43%
25-34	20.75%	11.43%
35-44	18.87%	9.05%
45-54	27.36%	19.29%
55-64	21.07%	15.48%
65-74	4.72%	3.81%
75+	0.31%	0.71%
Education Level		
Less than sigh school	0.31%	0.75%
High school graduate	1.57%	6.00%
Some college	8.18%	16.00%
Associate degree	1.57%	3.75%
Bachelor's degree	30.82%	25.75%
Graduate or professional degree	56.60%	47.75%
Annual Household Income		
Less than $10,000	0.94%	2.86%
$10,000 - $14,999	0.94%	1.19%
$15,000 - $29,999	2.83%	2.14%
$30,000 - $49,999	5.97%	7.86%
$50,000 - $74,999	8.81%	14.52%
$75,000 - $99,999	11.64%	15.95%

$100,000 - $149,999	21.07%	20.95%
$150,000 - $199,999	17.92%	15.48%
$200,000 or more	24.21%	11.67%
Counts	318	420
Response rate	36.34%	35.62%

Table 2 summarized the characteristics of the particular trips respondents were making when the questionnaires were handed out. Because of the survey questionnaires were handed out during the peak periods, it is no surprise that the majority of them were commuters. However, only 54% of them in surge 1 and 51% in surge 2 said they had to make the trip every workday. The rest of the participants did have some flexibility. About 40% respondents in surge 1 and 52% in surge 2 drove to the metro stations by themselves, while another 15% in surge 1 and 10% in surge 2 were dropped off. About 15% in Surge 1 and 10% in Surge 2 accessed the metro through buses. About 27% in both surges accessed the metro through walking, a very small percentage through biking or other modes. The difference in access modes may constrain metro riders from making certain choices during the SafeTrack.

Table 2 Trip Characteristics

Purpose of Trip	Surge 1	Surge 2
Commute	88.99%	81.19%
Leisure	2.83%	2.62%
Business	6.92%	13.81%
Others	1.26%	1.43%
Frequency of Metro Trips		
Every day	19.50%	23.57%
Every Workday	54.09%	51.19%

Less than once a Week	3.77%	4.05%
Once a Week	2.20%	1.19%
2-4 times a Week	20.13%	19.05%
Access the Metro		
Walking	27.67%	26.67%
Park and Ride	39.62%	52.14%
Bike	1.89%	0.24%
Other Mode	0.63%	0.48%
Dropped by Someone	15.09%	9.29%
Bus/Shuttle	15.09%	10.24%

Table 3 summarized the stated responses to the planned metro shutdown. Although the Metro will provide shuttle buses to bridge metro riders between affected stations during the SafeTrack project, it will add additional delays due to slower speed and additional transfer time on top of the delays the longer headways could cause. Therefore, only about 27% said they would stick to the original travel plan. More respondents in Surge 2 (39%) said they would change mode, while the majority respondents in Surge 1 (35%) change departure time. A significant portion (15%) of Surge 2 respondents said they would change destination because of the SafeTrack project, while the number is relatively small in Surge 1 survey. These differences could be related to the different nature of capacity reduction in Surge 1, and the complete service shutdown in Surge 2 for the affected metro line segment. Travelers may adjust their departure time to tolerate longer travel time, but they may dislike switching to the shuttle buses, which could add additional inconvenience due to transferring.

Table 3 Stated responses to the planned metro service disruptions

Pre Survey		
Change in Travel Behavior	Surge 1	Surge 2
No Change	27.04%	26.47%
Change Departure Time	35.22%	12.50%
Change to Other Travel Mode	27.99%	39.46%
Cancel the Trip	5.03%	6.37%
Change Destination to Avoid this Metro Line	3.14%	15.20%
Count	318	420

Figure 3 and 4 further decompose the stated reactions by income groups. In both surges, higher percentage of higher income riders would choose to change mode, while more low-income riders would choose no changes. The trend is more obvious in surge 2, where lower income riders were better represented. In addition, compared to the lower income groups, higher income groups are more likely to cancel trips, or change destination. These differences in behavior reactions could be due to the difference in value of time, and the flexibility in working schedules and locations among different income groups.

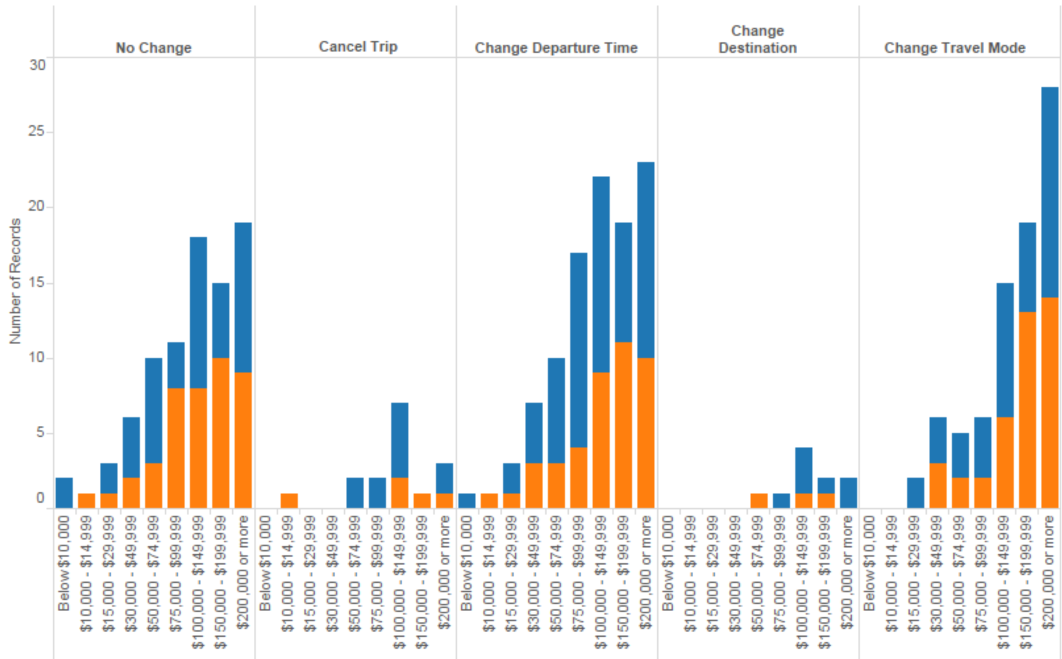


Figure 3 Reactions to SafeTrack Surge 1 (capacity reduction) by income groups

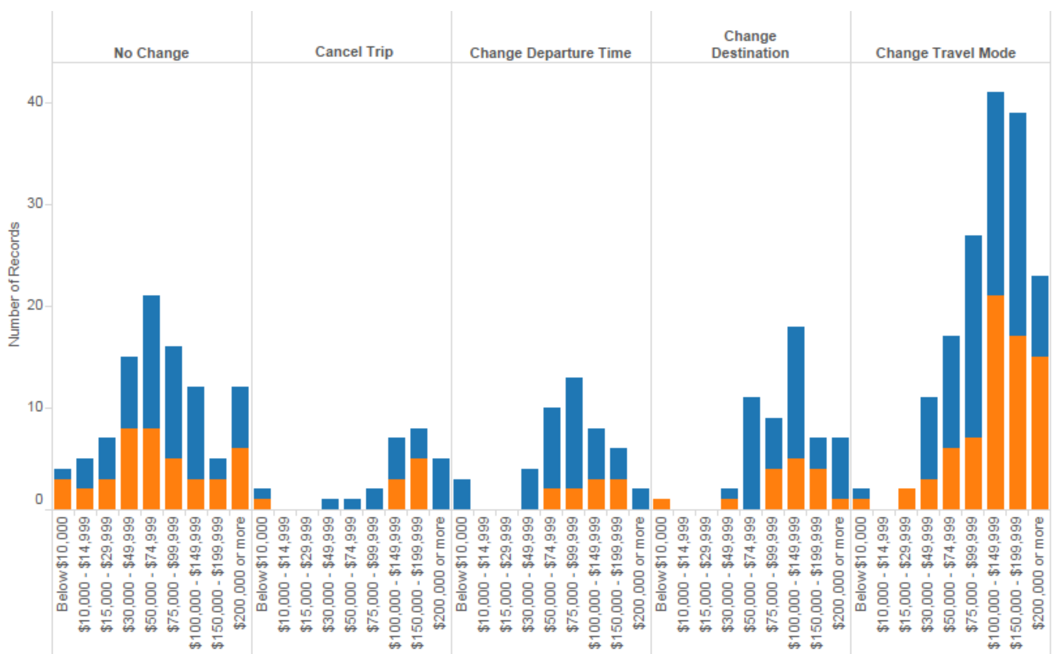


Figure 4 Reactions to SafeTrack Surge2 (segment shutdown) by income groups

Figure 5 further compares the preference for alternative modes among those who chose switching travel mode in reaction to the metro shutdown in both surges. It clearly showed that driving alone is the most preferred alternative for metro riders with a household income of $50,000 or higher. A detectable proportion of metro riders, especially for those with a household income of $150,000 or higher, would choose on-demand modes such as Uber and Lyft. However, most respondents in low-income groups (household income of $50,000 or lower) would choose regular bus as the most preferred alternative. In addition, the diversity for their choices is much lower. This may reveal the limitation in mobility for low-income groups and the importance of reliability transit services for them. However, due to the low representativeness of low-income groups among all survey respondents, more data is needed to draw conclusions that are more convincing.

A significant portion of respondents chose the other option, which included Loudon County Bus, Metro Blue Line, FCC Route Bus and mostly Virginia Rail Express in Surge 1, and MARC Train (the majority), Metro Green Line, Red Line, and Commuter bus in Surge 2.

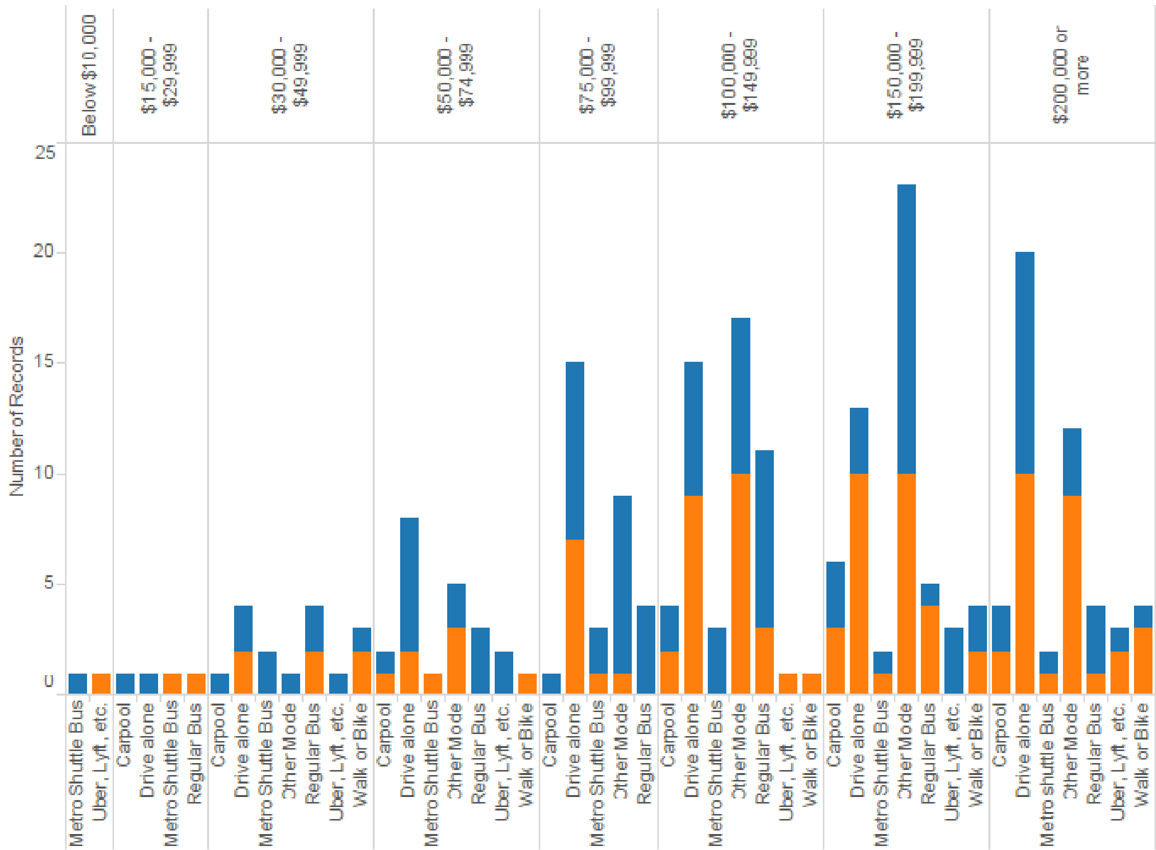


Figure 5 Mode choices among those who chose to switch modes in reaction to Metro SafeTrack surge 1 and 2 by income groups

FOLLOW-UP SURVEY RESULTS

A survey questionnaire with a pre-paid envelop was mailed out to the pre-survey respondents who indicated that they would be willing to complete a follow up survey. Totally 167 and 222 follow-up questionnaires were mailed for Surge 1 and Surge 2 respondents, respectively. Among them, 74 respondents from Surge 1 and 68 from Surge 2 completed the follow-up survey. A unique ID has been assigned to each respondent, which was used to link responses in the pre and follow-up survey to form a travel behavior panel.

Table 4 compared the preferred responses and the actual travel choices metro riders made during the SafeTrack surge. For example, only 15% of metro riders who said they would stick to their usual travel plans actually did so in Surge 1. The majority of the rest adjusted their departure time instead. All riders who stated that they would cancel trips or change destination actually did so. Only about one third of respondents who said they would change modes actually did it, while about one third of them changed their departure time instead. Similar patterns can be observed among Surge 2 respondents. However, more Surge 2 respondents chose to switch modes instead of changing departure time after they had the experience. This could be because the delay of using the bridging shuttle buses would be too long to be accommodated by departing earlier.

Table 4 Comparison between stated preference and the actual travel choices in response to SafeTrack Surge 1 and Surge 2 projects

Surge 1					
Pre Survey	Recall Survey				
	No Change	Cancelled Trip	Change Departure Time	Changed Destination	Changed to Other Mode
No Change in Travel Plan	15.00%		45.00%	25.00%	15.00%
Yes, I will cancel this trip		100.00%			
Change Departure Time	19.05%	19.05%	38.10%	19.05%	4.76%
Change my Destination				100.00%	
Change to Another Travel Mode	11.11%		33.33%	16.67%	38.89%
Surge 2					
Pre Survey	Recall Survey				
	No Change	Cancelled Trip	Change Departure Time	Changed Destination	Changed to Other Mode
No Change in Travel Plan	35.29%	5.88%	17.65%	11.76%	29.41%
Yes, I will cancel this trip		100.00%			
Change Departure Time		20.00%	20.00%		60.00%
Change my Destination			22.22%	33.33%	44.44%
Change to Another Travel Mode	8.33%	12.50%	16.67%	4.17%	58.33%

Most respondents explored several options before choosing the best response for them. Figure 6 showed the number of options respondents tried during the learning and adaptation process. Most of metro riders are commuters who are familiar with the transportation in the region. However, still more than half tried at least one alternative travel option. This number is an under-statement of the number of alternatives respondents actually tried since they could try more than one alternative modes, or alternative departure time, which could only be counted as one alternative in Figure 6.

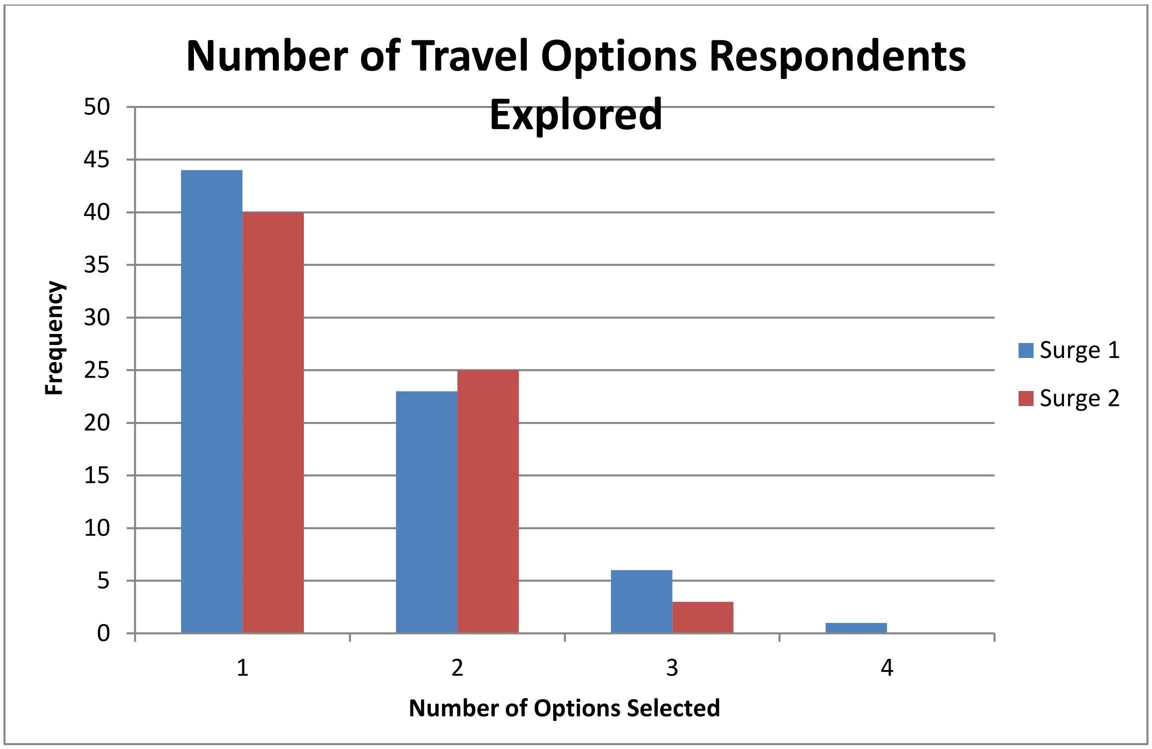


Figure 6 Number of options metro riders explored before choosing the most preferred response (1. canceled my trip and/or telecommuted, 2. change nothing, 3. change modes, 4. change destination, and 5. change departure time while still using the metro)

Figure 7 illustrated the percentage of respondents who have explored each alternative modes during the safe surge. Consistent with previous analysis, more people explored the metro services in Surge 1 compared to Surge 2. About 20% of them explored the option of driving alone, while slightly less travelers explored the carpool options. Respondents who tried regular taxi services was comparable with respondents who tried emerging on-demand services such as Uber and Lyft.

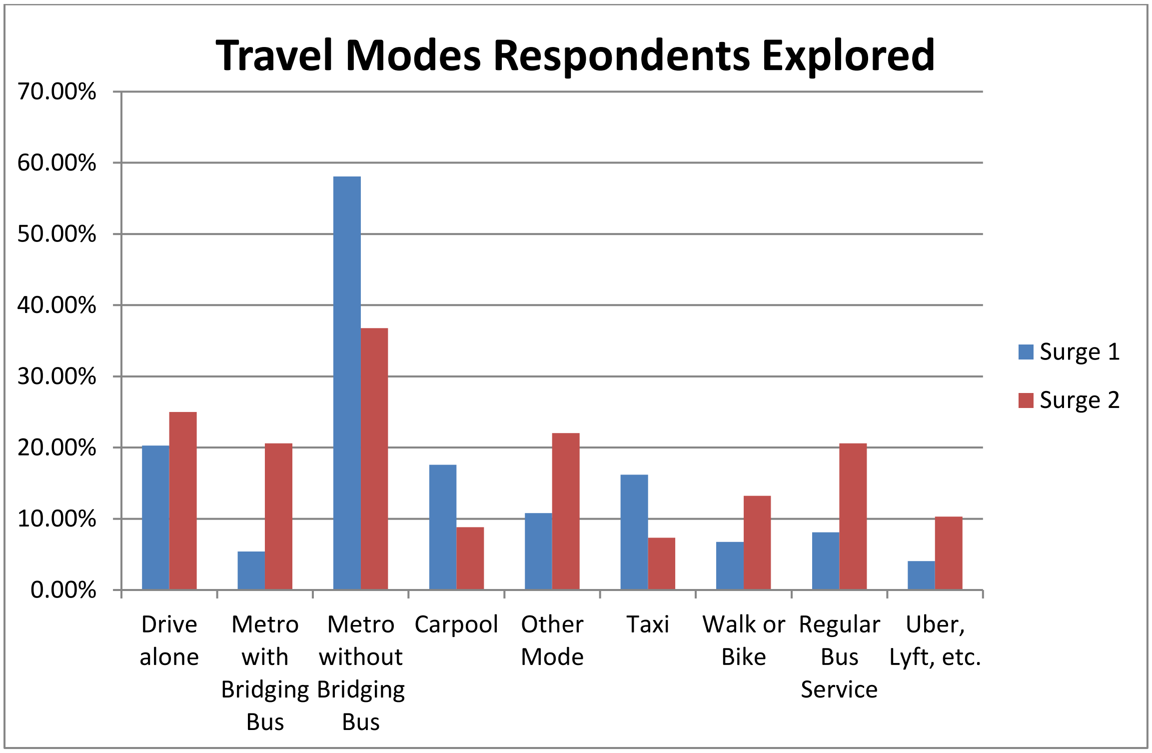


Figure 7 Travel modes respondents explored during the SafeTrack Surge 1 and Surge 2

Many previous studies argued that transit service disruptions could have long-term impact on travel choices even after the services are fully restored. Table 5 summarized the travel options respondents stayed with after the SafeTrack project. About 80% of the survey respondents rode metro after the services were fully restored. Carpool, driving alone, and regular bus each took about 3% of respondents, while the rest went to non-motorized modes or for-hire modes. Further research is needed to see if the reported behavioral changes are temporary, or will last for a significant longer time.

Table 5 Travel mode respondents stayed with after the SafeTrack project

Change in Travel Mode after Safe Track Surge		
	Surge 1	Surge 2
Carpool	3.03%	3.23%
Drive alone	3.03%	3.23%
Metrorail	78.79%	80.65%
Other Mode	3.03%	6.45%
Regular Bus Service	3.03%	4.84%
Taxi	1.52%	0%
Uber, Lyft, etc.	3.03%	0%
Walk or bike	4.55%	1.61%
Total	74	68

CONCLUSIONS BASED ON QUALITATIVE ANALYSIS

This study investigated behavioral reactions to transit service disruptions during the SafeTrack project of the Washington D.C. Metro system. Survey questionnaires with pre-paid envelope and QR code linking to a survey website were distributed among metro rider's at the most severely affected Metro stations before the planned projects. Follow-up surveys were mailed to respondents who agreed to do a follow-up survey on their actual travel choices during the metro-shutdown. Respondent IDs were used to link responses to both surveys, which form a unique travel choices panel dataset.

The majority of survey respondents were commuters and tend to have fairly high income and education levels, which are consistent with the general demographic profiles of metro riders in the affected area. The three most common reactions to the metro service disruptions are staying the same, changing mode, and changing departure time. However, Surge 1 differs from Surge 2 in that it involves only capacity reductions instead of complete metro station shutdown. Although bridging buses were provided in both cases, it involves additional inconveniences such as walking out of the platform, waiting for bridging buses, and over-crowded buses. Therefore, more people chose to change modes or destinations instead of changing departure time in Surge 2.

Income also played a significant role in determining the travel pattern changes. Wealthier riders are more likely to choose drive alone, or switching to for-hire modes such as Uber and Lyft, while low-income groups are more likely to choose regular bus services, or stick to the original travel plan. Value of time and affordability may play a role. This observation illustrates the important of investigating travel behavior of low-income groups during transit service disruptions, which is usually under-represented. With transit often being the primary travel modes for the lower-income population, such studies are critical for mitigating the impact to disadvantaged groups during the service disruptions.

More than half of the survey respondents tried more than one option before choosing the most preferable one, although most of them are fairly familiar with the region. A significant portion of respondents tried different modes. Many of them did not choose the option they stated in the pre-survey, which illustrates the importance of using the panel data approach to investigate behavioral changes in response to transit service disruptions. It also illustrates that stated-preference survey may not be a reliable tool for developing mitigation plans. More empirical studies on transit network disruptions are needed to prepare transit agencies struggling with aging infrastructure.

The survey showed that about 20% of respondents did not go back to the Metro system even after the service was fully restored. More research is needed to show to what extent these changes are related to the travel experiences during the service disruptions, and whether such effects are temporary or permanent.

A HIERACHICAL TRAVEL CHOICE MODEL

In the event of transit service disruptions, affected transit riders may react by adjusting their routes, departure times, travel modes, destinations, and/or cancelling trips, ranging from the easiest to the most drastic changes. Given the structure of the Washington Metro network, adjusting routes was not an option for most surges. In addition, travelers might decide to do nothing and simply accepted the new reality during the SafeTrack. In the literature, very few studies analyzed the traffic and behavioral impact of transit network disruptions. Among a few exceptions, most studies only provided descriptive analysis based on either survey data or aggregated traffic and transit ridership data (Zhu and Levinson, 2012). Such descriptive analysis could only offer limited help to transit agencies that are struggling to prepare for future events. To fill this gap, this study will develop a decision tree model to predict how travelers planned to deal with transit network disruptions.

Although travelers may not explicitly go through a hierarchical selection process to consider travel choices during major network disruptions, they may still give preferences to the alternative that is least disruptive to their travel routines (Zhu et al. 2010; Zhu and Levinson, 2015). Such a hierarchical choice structure has been used in transportation studies for a long time, dating back at least to the genesis of four-step planning modes. Following such a convention, this study also adopts a hierarchical structure and models travel choice in reaction to transit network disruptions through a series of decision. To facilitate the calculation of odds ratio, we order the choices from the most to the least drastic changes. Figure 08 summarizes the overall structure of the hierarchical travel choice model.

Travel decisions were treated as a series of binary choices and the probability for making certain travel choices can be decomposed as the product of corresponding conditional probabilities. For example, the probability for choosing an alternative destination is the product of the probability of not cancelling trips and the probability of changing destination given that the subjects have chosen not to cancel trips.

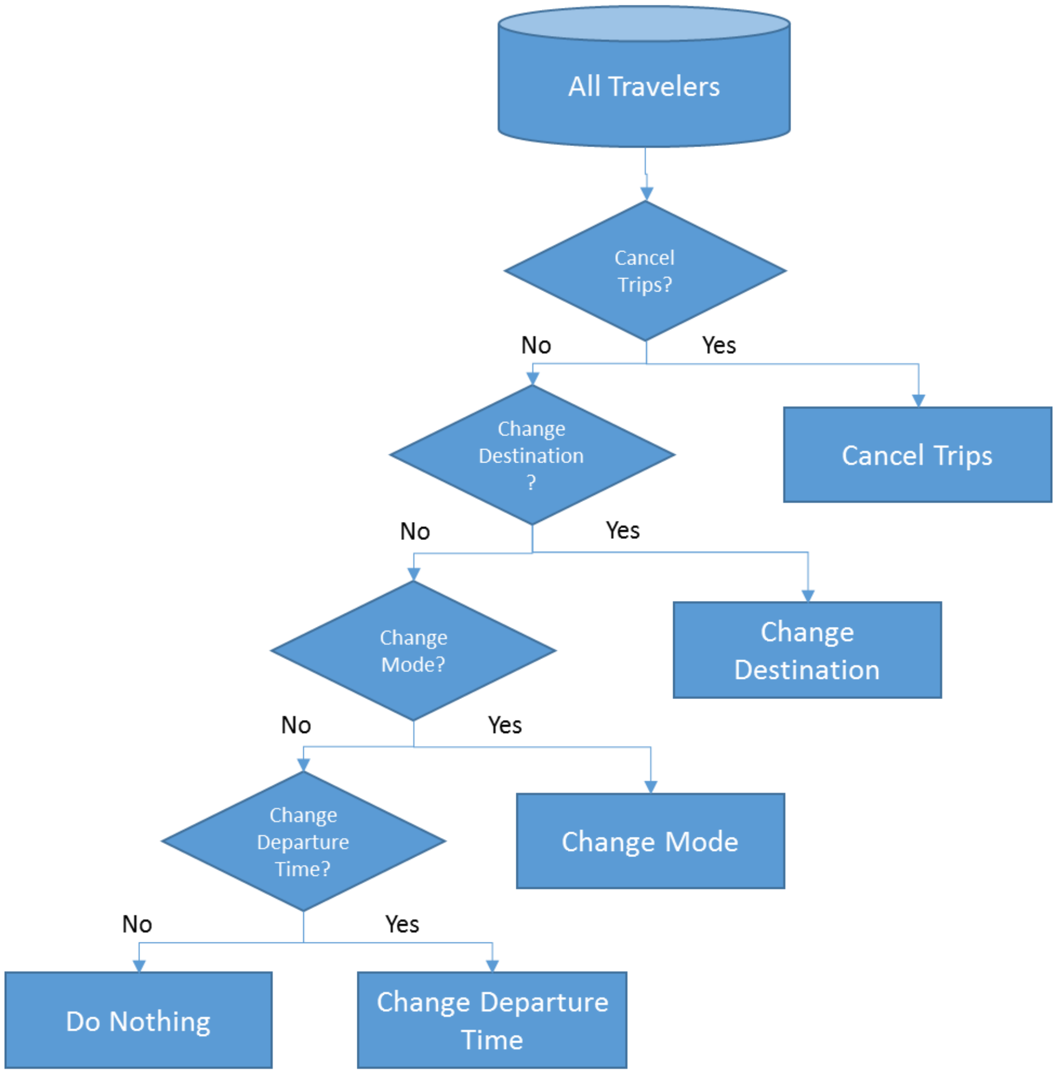


Figure 8 Overall Structure of the Hierarchical Travel Choice Model

There are many studies in the literature showing that travelers may not be able to well plan and plan for travel choices during a major network disruption. Therefore, the actual choice data is more preferable than the stated preferences data for developing travel choice models. However, data availability is always a major challenge for studies based on revealed preferences. To ensure enough number of subjects in each choice categories, this study used the stated preference data collected in the survey before each surges of the SafeTrack project. Future studies should explore the feasibility of developing similar models using actual choice data.

The following sub-sections will present the data, model estimation process, and the results for each layer of the hierarchical travel choice model.

Level 01: Cancel Trip

The first layer is whether a traveler would choose to cancel trips (including telecommute) or not. Samples used in this layer include all valid subjects (no missing information on either choices or social demographics) and the total number is 2635 (Table 6). As stated before, the travel decision is coded as a binary variable (Table 7), which is correlated with a series of independent variables shown in Table 8. Overall, 6% of respondents stated that they planned to cancel trips because of the SafeTrack.

Table 6 Case Processing Summary (Cancel Trip Model)

Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	2635	100.0
	Missing Cases	0	.0
	Total	2635	100.0
Unselected Cases		0	.0
Total		2635	100.0
a. If weight is in effect, see classification table for the total number of cases.			

Table 7 Dependent Variable Encoding (Cancel Trip Model)

Original Value		Code	Percentage
Cancel Trip	No	0	94%
	Yes	1	6%

Table 8 Categorical Variables Coding's (Cancel Trip Model)

		Frequency	Parameter coding (1)
Income	High Income	1545	1.000
	Medium Income	1090	.000
Type of Trip	Commuter Trips	2540	1.000
	Non-Commuter Trips	95	.000
Frequency of Trips	1-4 times a Week	540	1.000
	Every workday	2095	.000
Access the Metro Station	Bike/Bus	1442	1.000
	Kiss & Ride & Park & Ride	1193	.000
Extent of Information about Safetrack	Don't know about Safetrack	73	1.000
	Know about Safetrack	2562	.000
Gender	Female	1534	1.000
	Male	1101	.000
Education	Bachelors/Graduate Degree	2279	1.000
	College/High School	356	.000
Age	15-44	1339	1.000
	45-65	1296	.000
Surge Type	Line Segment Shutdown	1196	1.000
	Continuous Single Tracking	1439	.000

Table 9 Variables in the Equation (Cancel Trip Model)

		B	S.E.	Sig.	Exp(B)
Level 01	Surge Type (1)	.258*	.166	.121	1.294
	Type of Trip(1)	.528	.490	.281	1.696
	Frequency of Trips(1)	.722***	.183	.000	2.059
	Access the Metro Station(1)	-.131	.168	.436	.877
	Extent of Information about Safetrack(1)	.654	.417	.117	1.922
	Gender(1)	.111	.170	.516	1.117
	Age(1)	.026	.171	.877	1.027
	Education(1)	.218	.282	.440	1.244
	Income(1)	.437***	.193	.023	1.549
	Constant	-4.069	.585	.000	.017
Likelihood ratio test at 95% confidence interval * Significant at 90% **Significant at 95% ***Significant at 99%					

Level 01: Cancelling Trip Model Conclusion

A logistic regression was performed to test the effects of rider's income, type of metro trips, frequency of metro trips, mode used by rider to access the metro station, extent of information about SafeTrack that rider had, rider's education, rider's age, and SafeTrack surge type on the likelihood that the metro riders cancel their trip. The logistic regression model was statistically significant. The model shows the metro riders who travelled by metro 1-4 times a week were 2.059 times more likely to cancel their trip than riders who travel by metro every workday. Increasing income (high-income riders; >$100,000) was also associated with an increased likelihood of cancelling the trip by 1.59 times than medium income (<$100,000). Travelers facing a complete segment shutdown scenario were 1.29 times more likely to cancel trips than their counterparts facing a single-track operation scenario. Other variables, including trip purposes, accessing mode to metro stations, gender, age, education, and knowledge about the upcoming surges, were not significantly correlated with the likelihood of cancelling trips.

Level 02: Change Destination

Table 10 Dependent Variable Encoding (Change Destination Model)

Original Value		Code	Percentage
Change Destination	No	0	91.4%
	Yes	1	8.6%

Table 11 Variables in the Equation (Change Destination Model)

		B	S.E.	Sig.	Exp(B)
Level 02	Surge Type (1)	.730***	.149	.000	2.076
	Type of Trip(1)	-.089	.411	.828	.914
	Frequency of Trips(1)	-.043	.197	.829	.958
	Access the Metro Station(1)	-.528***	.149	.000	.590
	Extent of Information about Safetrack(1)	.296	.419	.480	1.345
	Gender(1)	-.070	.151	.641	.932
	Age(1)	.031	.151	.838	1.031
	Education(1)	-.381**	.195	.051	.683
	Income(1)	-.013	.161	.937	.987
	Constant	-2.052	.474	.000	.128
Likelihood ratio test at 95% confidence interval * Significant at 90% **Significant at 95% ***Significant at 99%					

Level 02: Changing Destination

Similarly, a logistic regression was performed to investigate the effects of rider's income, type of metro trips, frequency of metro trips, mode used by rider to access the metro station, extent of information about SafeTrack that rider had, rider's education, rider's age, and SafeTrack surge type on the likelihood that that the metro riders change their destination. The model showed that metro riders who experience a line segment shutdown during particular SafeTrack surge were 2.076 times more likely to change their destination than riders who experienced single tracking during particular SafeTrack surge. Metro riders who accessed the metro station using a bike/bus were associated with a decreased likelihood of changing their destination metro station by .590 times than those riders who accessed using Kiss & Ride or Park & Ride service, who had more flexibility in their choices.

Level 03: Change Mode

Table 12 Dependent Variable Encoding (Change Mode Model)

Original Value		Code	Percentage
Change Mode	No	0	62.1%
	Yes	1	37.9%

Table 13 Variables in the Equation (Change Mode Model)

		B	S.E.	Sig.	Exp(B)
Level 03	Surge Type (1)	.876***	.092	.000	2.402
	Type of Trip(1)	.034	.254	.892	1.035

	Frequency of Trips(1)	.593***	.117	.000	1.810
	Access the Metro Station(1)	-.346***	.093	.000	.708
	Extent of Information about Safetrack(1)	-.402	.308	.192	.669
	Gender(1)	-.045	.093	.627	.956
	Age(1)	.237***	.094	.012	1.268
	Education(1)	.127	.143	.373	1.136
	Income(1)	.591***	.101	.000	1.805
	Constant	-1.410	.302	.000	.244
Likelihood ratio test at 95% confidence interval * Significant at 90% **Significant at 95% ***Significant at 99%					

Level 03: Changing Mode

A logistic regression was performed to investigate the effects of Income, type of trips, frequency of trips, mode to access the metro station, extent of information about SafeTrack, education, age, and surge type on the likelihood that the metro riders Change their Mode. The model shows that metro riders who experience a line segment shutdown during particular SafeTrack surge were 2.402 times more likely to change their mode than riders who experienced single tracking during particular SafeTrack surge. Metro Riders who travel by metro 1-4 times a week were 1.8 times more likely to change their mode than riders who travel by metro every workday. Metro riders who accessed the metro station using a bike/bus were associated with a decreased likelihood of changing their mode (metro train) by .708 times than those riders who accessed using Kiss & Ride or Park & Ride service. Metro riders who were 15-44 years old were associated with an increased likelihood of changing their mode by 1.268 times than those riders who were

45+. High-income Metro riders (>100,000+) were also associated with an increased likelihood of changing their mode by 1.805 times than those riders with medium income (<100,000).

Level 04: Change Departure Time

Table 14 Dependent Variable Encoding (Change Departure Time Model)

Original Value		Code	Percentage
Change Departure Time	No	0	56.8%
	Yes	1	43.2%

Table 15 Variables in the Equation (Change Departure Time Model)

		B	S.E.	Sig.	Exp(B)
Level 04	Surge Type (1)	-.431***	.116	.000	.650
	Type of Trip(1)	.371	.348	.286	1.450
	Frequency of Trips(1)	-.331**	.161	.040	.718
	Access the Metro Station(1)	-.150	.114	.187	.861
	Extent of Information about Safetrack(1)	-.507	.343	.139	.602
	Age(1)	.313***	.114	.006	1.367
	Education(1)	.371**	.168	.027	1.449
	Income(1)	-.119	.118	.313	.887
	Constant	-.737	.389	.058	.478
Likelihood ratio test at 95% confidence interval * Significant at 90% **Significant at 95% ***Significant at 99%					

Level 04: Changing Departure Time Model

A logistic regression was performed to ascertain the effects of Income, type of trips, frequency of trips, mode to access the metro station, extent of information about SafeTrack, education, age, and surge type on the likelihood that the metro riders Change their Departure Time. Metro Riders who experience a line segment shutdown during particular SafeTrack surge were 0.650 times less likely to change their departure time than riders who experienced single tracking during particular SafeTrack surge. Metro Riders who travel by metro 1-4 times a week were .718 times less likely to changing their departure time than riders who travel by metro every workday. Metro riders who were 15-44 years old were associated with an increased likelihood of changing their departure time by 1.367 times than those riders who were 45+. Highly qualified Metro riders (with bachelors/graduate degree) were also associated with an increased likelihood of changing their departure time by 1.449 times than those riders with some college of high school education.

Aggregated Impact through the Hierarchical Model

Through each layer of this hierarchical travel choice model, we could assess the impact of every independent variables on the likelihood of respondents choosing a travel choice given that they have chosen “No” for all layers above and have arrived that this layer through the hierarchical decision making mechanism. To fully assess the unconditional impact of a social demographic variable on the likelihood for a respondent to choose a particular alternative in response to the transit network disruption, we need to evaluate its impact on the odds ratio for each layer of decisions above and calculate the compound odd ratio associated with that independent variable. Table 17 summarizes such impact on each choice.

Table 16 Absolute Probability

Behavioral Reaction	Percentage
No change to Trip	30.39%
Cancel Trip	6.01%
Change Destination	8.10%
Change Mode	32.14%
Change Departure Time	23.35%

Binary logistic regression analyses often have response variables with two possible levels out of which one is the desired outcome. Such kind of logistic regression allows predicting the probability of the desired outcome and determining which independent variables are most closely related to the outcome. This regression produces odd ratios, which in turn provide a measure of the effect on that particular outcome. Rather than focusing on the value of the parameter estimates, binary logistic regression often focuses on odds and odd ratios.

Table 17 Marginal Probabilities

	Income	Frequency of Trips	Access the Metro Station	Education	Age	Surge Type
Level 01: Cancel Trip	1.549	2.059	1.000	1.000	1.000	1.000
Level 02: Change Destination	0.645	0.485	0.590	0.683	1.000	2.076

Level 03: Change Mode	1.805	1.810	0.708	1.464	1.268	2.402
Level 04: Change Departure Time	0.550	0.718	1.280	1.449	1.367	0.650
Level 05: No Change	0.991	1.297	0.534	1.448	1.733	3.241

If we extend the analysis onto level 3 and 4, which are changing mode and changing departure time, the absolute probability of a rider can be obtained as $P_0 = P_1 \times P_2 \times P_3 \times P_4$ which is the product of individual probabilities at a particular level.

CONCLUSIONS

This study investigated behavioral reactions to transit service disruptions during the SafeTrack project of the Washington D.C. Metro system using data collected through a panel survey. The majority of survey respondents were commuters and tend to have fairly high income and education levels, which are consistent with the general demographic profiles of metro riders in the affected area. The three most common reactions to the metro service disruptions are staying the same, changing mode, and changing departure time. However, Surge 1 differs from Surge 2 in that it involves only capacity reductions instead of complete metro station shutdown. Although bridging buses were provided in both cases, it involves additional inconveniences such as walking out of the platform, waiting for bridging buses, and over-crowded buses. Therefore, more people chose to change modes or destinations instead of changing departure time in Surge 2.

Income also played a significant role in determining the travel pattern changes. Wealthier riders are more likely to choose drive alone, or switching to for-hire modes such as Uber and Lyft, while low-income groups are more likely to choose regular bus services, or stick to the original travel plan. Value of time and affordability may play a role. This observation illustrates the important of investigating travel behavior of low-income groups during transit service disruptions, which is usually under-represented. With transit often being the primary travel modes for the lower-income population, such studies are critical for mitigating the impact to disadvantaged groups during the service disruptions.

This study further investigated the factors that would affect planned travel choices among survey respondents during the SafeTrack through quantitative analysis. A hierarchical travel choice model, which includes four layers of logit regression models, was developed to assess the impact of social demographic factors on travel choices (cancel trips, change destination, change mode, change departure time, do nothing). The model allows us to assess the conditional impact of different social demographic factors on the choice of the particular layer, and the unconditional impact by aggregating the impact through the decision tree. Through this process, Surge type, Frequency metro trips and income has a significant impact on the behavioral decision of rider. Higher income has a positive impact of riders choice to either cancel trip or change departure time while higher frequency of trips (trips every weekday) has a greater impact on the decision of rider at each level.

Future studies will further expand the sample size and use the actual choice data instead of the stated preference data for model development. Models developed in such studies could help agencies who are struggling with aging infrastructure to better evaluate the potential impact and better prepare for future events.

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BIOGRAPHY

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