Transit Information Utilization during an Extreme Weather Event: An Analysis of Smartphone App Data

Word Count: 5,352 (text) + 250 * 7 (figures) = 7,102

Submission Date: November 15, 2017

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ABSTRACT

Extreme weather events such as heavy snow can severely disrupt urban transportation systems. When this occurs, travelers often seek information about the status of transportation services. This study aims to assess information utilization during an extreme weather event by analyzing data from a smartphone application (“app”) called Transit, which provides real-time transit and shared mobility information in many cities. This research focuses on a snowstorm that hit the northeastern USA in January 2016 and severely disrupted transit and shared mobility services. An analysis of Transit app data is conducted in four parts for New York City, Philadelphia, and Washington, D.C.

First, hourly app utilization during the snowstorm is compared to mean hourly app utilization prior to the storm. Second, the rate of app usage is calculated by dividing hourly utilization during the storm by the mean hourly volume before the storm. Third, an ordinary least squares regression model of hourly app usage was estimated for each city. Last, a feature within the app used to request Uber vehicles was examined. The results of the first three analyses reveal that overall app usage decreased during the snowstorm in all three cities; after the storm, New York experienced a significant increase in overall app use during the first Monday commuting period. The analysis of Uber data reveals that app users continued to search for ridehailing services during the snowstorm, despite travel bans. These findings are important for transportation operators and app developers to understand how travelers use information during extreme weather events.
INTRODUCTION

Extreme weather events such as heavy snow can severely disrupt urban transportation systems. One recent example occurred in January 2016, when Winter Storm Jonas dumped historic amounts of snow throughout the northeastern region of the United States. Jonas was the single largest snowstorm on record for numerous locations in the northeast, including New York City’s LaGuardia Airport and Baltimore-Washington International Airport (1). This historic snowfall deeply affected the transportation systems in New York City (NYC), Philadelphia (PHI), and Washington, D.C. (DC). The local governments declared travel bans, public transit systems were shut down, and the period of recovery in some areas lasted for nearly a week after the snowstorm.

When extreme weather events such as Winter Storm Jonas occur, travelers often seek information about the status of transportation services to determine if they are shut down and to stay informed as they reopen. However, understanding how travelers seek information during extreme events can be challenging due to a lack of readily available data. For example, surveys are difficult to administer during unplanned events, and they can be expensive to collect retroactively. Therefore, this research aims to use a new data source to understand how travelers seek information during an extreme weather event. Specifically, the records from an urban transportation information smartphone application (or “app”) are examined to provide insight into how travelers utilize new information and communication technologies during severe storms.

PRIOR RESEARCH AND OBJECTIVES

There is a growing body of literature that examines the transportation system impacts of extreme weather events (e.g., 2, 3, 4) and large special events such as sports games (e.g., 5, 6). This brief review of prior research focuses specifically on studies that use new data sources to understand the impacts of extreme weather on the transportation system in the New York City region.

One noteworthy study measured the resilience of the New York City transportation system after Hurricane Sandy using data from taxi GPS traces (7). The findings suggest that Hurricane Sandy impacted roadway traffic conditions for more than five days, and that significant traffic delays were encountered during the post-disaster response period. A second noteworthy study used two “big data” sources to assess the consequences of Hurricane Sandy and Hurricane Irene in New York City (8). Post hurricane recovery patterns for the roadway and subway systems were analyzed using taxi trip data and subway turnstile data, respectively. The method involved calculating the rate of recovery, which was found to be lower for Hurricane Sandy compared to Hurricane Irene. A third study developed a method to detect demand fluctuations and correlate them with disruptive events (such as extreme weather conditions) using New York City taxi trip data (9).

In summary, there are a number of emerging data sources that can help to quantify the impacts of extreme events on transportation system performance. However, to the best of the authors’ knowledge, prior research has not considered the relationship between extreme events and transportation app utilization. Therefore, the objective of this study is to explore the use of transportation information provided via smartphone applications during an extreme weather event. The specific dataset used in this analysis is from a smartphone application called “Transit,” which is available in numerous cities (10, 11, 12). Because of the multi-city nature of the Transit app, the dataset allows for a comparison between three cities that were affected by the snowstorm of January 2016: New York City, Philadelphia, and Washington, D.C.
BACKGROUND ON THE WINTER STORM

Winter Storm Jonas paralyzed the eastern United States from Friday, January 22, 2016 to Sunday, January 24, 2016. Between 20 and 30 inches of snow accumulated in New York City, Philadelphia and Washington, D.C. (13). On Friday, January 22, government officials in Washington, D.C. declared a snow emergency (14), and the local government in Philadelphia did the same. The following day (January 23), officials in New York City declared a travel ban. In each of these three cities, transit services were gradually shutdown, beginning before the storm in some areas and resulting in a complete shutdown during the worst periods of the snowstorm. Additionally, Uber service was officially shutdown in New York City (15).

The hour-by-hour status of public transit and shared mobility services (specifically, Uber) before, during, and after the snowstorm are shown in Figure 1. This information was compiled from transportation authority websites, local media sources, and social media.
FIGURE 1 Timeline of the Snowstorm.
This section contains a general description of the smartphone app data used in this analysis. The first part gives a brief overview of the smartphone app, the second part defines the geographic area of analysis, and the last section includes a brief description of the data files.

Overview of the Smartphone Application
The Transit app is a smartphone application available on Android and iPhone that provides information about public transportation and shared mobility services, such as bikeshare, carshare, and ridehailing (10). The Transit app covers New York City, Philadelphia, Washington, D.C. and approximately 125 other cities. The app includes many features, such as real-time transit vehicle information (see left screenshot in Figure 2), trip planning (see right screenshot in Figure 2), transit service alerts, and multimodal support including Uber. When using the Uber feature, it should be noted that the user can click “request an Uber” in the Transit app, but s/he will be directed to Uber’s app to complete the Uber order.

Time Period and Geographic Area of Analysis
The time period for this study is Friday, January 8, 2016 to Friday, January 29, 2016; that is two weeks before the snowstorm and one week after. The geographic areas are the regions of New York City, Philadelphia, and Washington, D.C. The boundaries of the three regions were selected based on the Metropolitan Planning Organization areas (30, 31, 32, 33, 34). Specifically, three bounding boxes were drawn to define the maximum and minimum latitude and longitude for each area. The New York area includes the region served by the New York Metropolitan Transportation Council (NYMTC) (30) and the North Jersey Transportation Planning Authority (NJTPA) (31), which is shown in Figure 3 in yellow. The Philadelphia area includes the regions served by the New York Metropolitan Transportation Council (NYMTC) (30) and the North Jersey Transportation Planning Authority (NJTPA) (31), which is shown in Figure 3 in yellow. The Philadelphia area includes the regions served by the Delaware Valley Regional Planning commission (DVRPC) (33) and the South Jersey Transportation Planning Organization (SJTPO) (34), which is shown in green in Figure 3. Last, the Washington, D.C. area was selected using the region served by the Capital Region Transportation Planning Board (TPB) (32) shown in blue in Figure 3.
FIGURE 3 Bounding boxes around the New York City, Philadelphia, and Washington, D.C. Metropolitan Areas.

Data Description
The data used in this analysis was provided by the Transit app to the research team. The dataset contains user interactions with the app. Each time a user opens the apps, a unique session identifier (ID) is created, the time is recorded, and the location of the user (latitude/longitude) is stored. Between January 8 and January 29, 2016, there were millions of Transit app sessions in the areas of analysis.

The following analysis also uses a subset of the data that includes all Uber requests made through the Transit app. Each time users click to request an Uber in the Transit app, the user’s location (latitude/longitude) and the time of the request are recorded. Between January 8 and January 29, 2016, there were thousands of Uber requests in the areas of analysis.

ANALYSIS
An analysis of Transit app utilization during the January 2016 snowstorm was conducted in four parts. First, overall Transit app usage patterns were visually explored, and then the rate of use was calculated by comparing app use during the snowstorm to a regular period. Next, a regression model of total hourly app use was created. Last, the use of the Uber feature in the Transit app was investigated in a visual analysis. The results of this analysis are described in the following sections.
Part 1: Visualization of Transit App Usage

First, overall Transit app usage patterns were visually explored. During the three-week period of analysis, the total Transit app usage per hour in each region was calculated. This was then compared to the mean app usage per hour during the two first weeks before the snowstorm when there were normal weather conditions (January 8 to January 15).

Figure 4 shows hourly Transit app usage (the black line) compared to the mean hourly usage (the red line) for each of the three regions. Utilization of the app has a strong periodic weekly pattern. There is a peak during the morning rush hour and another during the evening rush hour for weekdays, and app usage decreases during the weekend. However, this typical pattern was interrupted during the snowstorm period, as can be seen in Figure 4. The vertical line in yellow shows the period when the snowstorm hit each of the three cities, and the vertical line in blue displays when the transit systems were closed. During this period, the amount of overall app usage per hour in each city was less than the mean. In the New York City area and in the Philadelphia area, this decrease is more pronounced on Saturday January 23 during the afternoon. For the Washington, D.C. area, the decrease in app usage began earlier (on Friday January 22) and stayed below the mean for longer than the two other areas.

Part 2: Rate of Transit App Use

Next, the rate of Transit app use was calculated in a similar manner to a previous paper on extreme events (8) by comparing mean hourly usage prior to the snowstorm with hourly app usage during the snowstorm for each city. For every hour $t$, the rate of use $R(t)$ was calculated by dividing the hourly app usage, $U(t)$, by the mean hourly usage, $Q(t)$, during the reference period, which was the two weeks before the snowstorm. Equation [1] shows the rate of use formula:

$$ R(t) = \frac{U(t)}{Q(t)} \quad [1] $$

Figure 5 displays the results of the rate of use calculation for each of the three cities as a black line. The red line in Figure 5 shows 100%, which is the typical usage during the reference period. As can be seen in Figure 5, the three cities generally exhibit similar patterns. The rate of use is fairly consistent during the two weeks prior to the storm, and all three cities have a dip in use on the Martin Luther King, Jr. holiday, which was Monday, January 18, 2016. During the snowstorm, all three cities initially exhibited an increase in the rate of use, but this quickly decreased below the 100% level as the snowstorm continued.

In New York City, the rate of app usage dropped below 100% on Saturday, January 23 before noon and remained low until the following day (Sunday, January 24). On Saturday, most transit service in New York City was shut down during the snowstorm (with the exception of some underground areas of the subway), and it was during this time that the rate of use reached its lowest point (approximately 65% of mean usage). After the snowstorm finished and transit service was largely restored on Monday, January 25, a peak appeared during the morning rush hour, and the rate of use reached about 165%. This may be because Transit app users wanted more information as they went back to work to assure them that transit service was fully restored.

In the Philadelphia area, the rate of Transit app use initially increased on Friday, January 22 around 12pm; at this time, a snow emergency had been declared (37) but the transit system had not yet shutdown. This spike in use is likely because Transit app users were searching for information to get home before the snowstorm. Shortly thereafter, during the nighttime on Friday,
January 22, the rate of use dropped substantially below 100% and stayed low until the morning of January 24, 2016. On Saturday 23, when Philadelphia transit authorities suspended all their services (Figure 1), the rate of use reached about 65% of the mean usage, which was the lowest point. After the snowstorm finished and transit service was largely restored on Monday, January 25, a small increase in the rate of use appeared during the morning rush hour.

In the Washington, D.C. area, the rate of Transit app use dropped below 100% for most hours from January 22 at noon until January 25 at midnight. After the storm, the rate of use took longer to stabilize compared to the other metropolitan areas, which may have been because the recovery time of the transit systems in this region was longer than the other areas (Figure 1). For example, it was not until Tuesday, January 26 that most of the Washington, D.C. metro system was reopened (with 86 of 91 Metrorail stations opened by Tuesday January 26). Consequently, app users in Washington, D.C. seemed to be more affected by the snowstorm than those in New York City or Philadelphia.

Finally, it should be noted that some peaks in Figure 5 are not meaningful due to data limitations. For example, a peak in the rate of use appeared in each of the three cities on Monday, January 11. This is because the other Monday used to calculate the mean (reference) hourly usage was Martin Luther King Day. Future analyses should expand the period of analysis to accommodate this.
FIGURE 4 App usage and mean usage in New York City, Philadelphia and Washington, D.C.

FIGURE 5 Rate of app use in New York City, Philadelphia and Washington, D.C.
Next, three Ordinary Least Squares (OLS) regression models were estimated: one for New York City, one for Philadelphia and one for Washington, D.C. In each regression model, the dependent variable is the number of Transit app records per hour in the corresponding city. For independent variables, eight binary variables were defined to account for the effects of Martin Luther King Day (on Monday January 18), three days of the snowstorm (Friday January 22 to Sunday January 24), and four days after the snowstorm (from Monday January 25 to Thursday January 28). Also, to control for the typical weekly app usage pattern, 167 binary variables were included in each model to account for the 168 hours in a week. Equation [2] below shows the regression model formulation, which is the same for each city (New York City, Philadelphia and Washington, D.C.):

$$Y_t = \alpha + \sum_{i=1}^{167} \beta_i h_i + \beta_{168} MLKD + \beta_{169} SD1 + \beta_{170} SD2 + \beta_{171} SD3 + \beta_{172} RD1 + \beta_{173} RD2 + \beta_{175} RD3 + \beta_{176} RD4$$

Where:
- $Y_t$ = Number of Transit app records per hour $t$
- $h_i$ to $h_{167}$ = Binary variables representing each hour of the week (i.e., $h_1$ represents Friday at 12am, $h_{25}$ represents Saturday at 12am, and $h_{167}$ represents Thursday at 11 pm)
- $MLKD$ = Binary variable representing Martin Luther King Day
- $SD1$ to $SD3$ = Binary variables representing the first, second, and third day of the snowstorm from Friday, January 22 to Sunday, January 24, respectively
- $RD1$ to $RD4$ = Binary variables representing the first to fourth days after the snowstorm from Monday, January 25 to Thursday, January 28

The results of the regression models for each city are presented in Table 1. All three models have high R-squared values, and more than 90% of variation in the data can be explained by the model for each city. The F-statistic is significant for each model, which confirms the high joint significance of the variables.

For the New York City regression model, all eight binary variables representing Martin Luther King Day, the snowstorm days, and recovery days are significant (p-value < 0.01); this means that holidays and extreme weather strongly affect Transit app utilization. The coefficient for Martin Luther King Day is negative (-3,843.750), suggesting that app usage decreases on holidays. On Friday, January 22, when the snowstorm first hit New York City, the number of Transit app records increased (coefficient of 2,773.521); this increase may be due to a perceived disruption in the transit system. However, on the second day of the storm when the transit system was shut down and a travel ban for motorists was imposed, Transit app usage decreased significantly (coefficient of -8,925.938). On the last day of the snowstorm, when motorists were allowed on the roads and the transit system began to reopen, the number of Transit app records increased (coefficient of 4,110.063). The greatest change in Transit app usage was observed on the first day after the snowstorm on Monday, January 25, which had a large positive coefficient (9,709.958). On this day, users were likely searching for transit information for their commute trip. On the subsequent days after the snowstorm, Transit app usage was larger than usage on
normal days, which is indicated by the positive significant coefficients on the second, third, and fourth recovery days (7,013.187, 4,903.354, and 3,544.271, respectively).

In Philadelphia, the binary variables representing Martin Luther King Day, the three days of the snowstorm, and the first day after the snowstorm were strongly significant (p-value < 0.01). The effect on Martin Luther King Day is similar to that observed in New York City; Transit app usage was less than normal days (coefficient of -576.625) on the holiday. On the first and second days of the snowstorm, app usage was higher than usual (coefficient of 381.437 and 2,200.625, respectively). On the last day of the snowstorm (Sunday, January 24), the number of Transit app records decreased, which is expected due to the transit system shut down over the weekend (coefficient of -389.958). The decrease in Transit app usage continued on the first day after the snowstorm (coefficient of -373.292) even though the transit system resumed service and it was a weekday (Monday, January 25). Two days after the snowstorm, the number of Transit app records increased, and this increase continued during the third day and fourth days of recovery after the storm.

In Washington, D.C., the coefficients are significant (p-value < 0.05) for the binary variables representing Martin Luther King Day, the three days of the snowstorm, and one day after the snowstorm. All of the coefficients for the storm days and the recovery days in this model are negative, which means that Transit app records decreased during the storm and continued to be lower than normal after the snowstorm. The transit system in Washington, D.C. resumed service on the first day after the snowstorm (Monday, January 25) but took longer to get back to normal. This model suggests that Washington, D.C. had the slowest recovery in Transit app usage of the three cities.
TABLE 1 Regression Results for New York City, Philadelphia & Washington, D.C.

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<td>Thurs. Jan. 28 (4th day after snowstorm)</td>
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<td>F Statistic (df = 175; 328)</td>
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Notes: *p<0.1; **p<0.05; ***p<0.01

Standard error shown in parenthesis.

167 hourly dummy variables not presented in the table; available upon request.

Part 4: Visualization of Uber Requests

Besides overall Transit app usage, Uber requests made through the app were also considered. The dataset contains all sessions in which a user opened the app and clicked on “Request an Uber.” However, users cannot book an Uber directly within the Transit app; instead, they are directed to Uber’s app for fulfillment. Consequently, the Transit app dataset only highlights the users’ intention of taking Uber and does not reflect actual Uber trips.

Figure 6 shows daily Uber requests through the Transit app and a comparison with the mean of the previous two weeks. The amount of data was very small compared to overall Transit app use; thus, the analysis was conducted on a daily basis instead of hourly. As can be seen in Figure 6, the yellow line shows when the snowstorm hit the three cities, the line in blue is when the transit systems were closed, and the line in green represents the travel ban or snow emergency period. It should be noted that in New York City, Uber service was officially suspended from Saturday, January 23 at 2:30 pm until Sunday, January 24 at 4 am (Figure 1). In Philadelphia and in Washington, D.C., a reference stating that Uber service was suspended could not be found;
however, the authorities asked citizens to stay off of the roads in both cities (34, 35), so it assumed that Uber was not operating during this time.

In New York City, the total number of Uber requests via the Transit app was between 300 and 600 per day during the reference period prior to the storm. Interestingly, the number of Uber requests was higher during the snowstorm period. On Sunday, January 24, the number of Uber requests reached a peak of 1,750 in New York City. In Philadelphia, the number is between 50 and 150 per day prior to the storm and reached 280 requests during the storm. For Washington, D.C., the number of Uber requests was between 75 and 180 per day prior to the storm, and the highest peak represented more than 300 requests on Monday, January 25. Unlike the two others cities, the lowest point in Washington, D.C. occurred on Saturday, January 23 when no vehicles were allowed on roads and the transit system was shut down.

The results imply that despite travel bans, the number of Uber requests was greater than usual. During the snowstorm, Transit app users were probably looking for other modes of travel when the transit systems were shut down. When the transit systems began to reopen service (on Sunday in New York City and in Philadelphia and on Monday in Washington, D.C.), the number of Uber requests via the Transit app reached the highest point. Last, it is important to emphasize that these are requests for Uber, which do not necessarily involve fulfilled trips; Transit app users are directed to Uber’s app for fulfillment.
CONCLUSIONS AND FUTURE RESEARCH

This study assessed information utilization during an extreme weather event by analyzing data from a smartphone app called Transit, which provides real-time transit and shared mobility information in many North American cities. The analysis focused on a snowstorm that hit the northeastern USA in January 2016 and severely disrupted transit and shared mobility services. A four-part analysis was conducted for three cities: New York City, Philadelphia, and Washington, D.C. First, hourly Transit app utilization during the snowstorm was compared to the mean hourly utilization prior to the storm. Second, the rate of app usage was calculated by dividing hourly utilization during the storm by the mean hourly volume before the storm. Third, an ordinary least squares regression model of hourly app usage was estimated for each city. Last, a feature within the app used to request Uber vehicles was examined.

The results of the first three analyses revealed that overall app usage decreased during the snowstorm in all three cities. After the storm, New York City experienced a significant increase in overall app use during the first Monday commuting period, and Washington, D.C. had the slowest recovery in app usage. The analysis of Uber data revealed that Transit app users continued to search for ridehailing services during the snowstorm, despite travel bans. Although some of the findings of this study are to be expected – such as the decrease in overall Transit app usage during the storm and an increase immediately afterward – the number of Transit app searches during the snowstorm was surprisingly large, particularly during the period when the transit systems were completely shut down (i.e., a decrease to only about 65% of mean use).
These findings are important for transportation operators and app developers to understand how travelers use information from smartphone apps during extreme weather events, which would be very difficult to do using traditional data sources such as surveys. This new type of technology—smartphone apps—largely did not exist a decade ago and has rapidly changed how transit agencies communicate with travelers. However, traveler utilization of this new technology—particularly during unusual or extreme events—has not been well documented. If usage patterns are better understood, it can help transit agencies to better communicate with travelers during extreme events and potentially help transit systems to recover faster by improving communication channels. This analysis shows that travelers want to be informed of changes in transportation service, as evidenced by large spikes in Transit app usage after the snowstorm, and therefore, transportation providers should anticipate increased communication levels immediately after extreme weather events. Transportation operators should also consider multiple means of communication (beyond just apps) to ensure that they reach all of the traveling public.

Last, many interesting areas for future research emerged from this analysis. First, the analysis of Winter Storm Jonas could be expanded to other regions, including areas that were not as heavily impacted by the snow as New York City, Philadelphia, and Washington, D.C. Another interesting area for future research is to examine Transit app usage patterns at the individual level, instead of at the metropolitan level. Additionally, the continuous nature of this dataset enables other anomalous events to be studied, including both planned events such as concerts or sports events and unplanned events such as hurricanes. Finally, it would be interesting to compare utilization of the Transit app to use of other transportation-related smartphone applications; however, in order for comparative analyses to be possible, the developers of other applications (which are often private companies) must be willing to share usage data. Hopefully there will be increased willingness to share data in the future as utilization of smartphone apps continues to grow.

ACKNOWLEDGEMENTS
The authors acknowledge the Transit app for sharing data, and they are particularly grateful to Jake Sion. This research was supported in part by a 2015 City University of New York (CUNY) Collaborative Incentive Research Grant (CIRG) grant and a 2016 University Transportation Research Center (UTRC) faculty-initiated grant.
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