December 10, 2018

Estimating Time and Cost Sensitivity in New Yorker's Transport Decisions: Evidence from the Second Avenue Subway

Applied Data Science Project

Guobing Chen, Fangshu Lin, Hao Xi, Nick Jones

Abstract:

This project analyzed how the Second Avenue Subway affected taxi journeys by New Yorkers. The topic is of interest because the opening of three new subway lines in January 2017 provides a 'natural experiment' that can be used to derive empirical findings on how large numbers of city residents changed their mobility patterns in response to the new facilities. We defined a treatment area (the Upper East Side to the east of the new stations) and a control area (Sutton Place/Turtle Bay North). A matrix of outgoing taxi journeys to other city destinations was constructed for both our treatment group (the Upper East Side to the east of the new stations) and our control group (Sutton Place/Turtle Bay North). A similar matrix was constructed for incoming journeys from these areas. Clustering analysis was performed to identify the groups of stations with significant changes in mobility patterns vis-a-vis the control area. We find significant decreases in taxi journeys to and from specific locations including Midtown, Upper West Side, Battery Park and Park Slope which are attributable to the new subway line. Our method has applications for transport planning and for evaluating whether public transit investments produced mobility benefits for different geographic regions of the city.

1. Introduction

On January 1, 2017, three new subway stations opened as part of the long-awaited Second Avenue Subway, bringing better mass transit facilities to a zone of the Upper East Side including Yorkville and Lenox Hill (Figure 1).

The new stations provide a rare opportunity to analyze how transport patterns among the city's population changed in response to the overnight availability of new public transport options. In this study, we make use of data available from the Taxi and Limousine Commission (TLC) to analyze to what extent New Yorkers switched from taxi to subway. Doing so allows us to detect patterns in transport choices between specific pairs of neighborhoods across the city. Examining the Second Avenue Subway extension provides an opportunity to test applications for transportation analysis using large urban datasets with relevance to a variety of planning decisions - including the likely utilization of more stations planned for the Second Avenue line and how the opening of those stations would affect connectivity economic vitality of neighborhoods that are newly connected to each other by a public transport option.

2. Literature Review

Modelling of user demand for different modes of transport is important for several policy issues, such as where to place subway stations, how to finance them, and how to ensure equitable access to transport that meets user needs. As such, an extensive literature has developed around transport demand modelling.

Transport demand models employed by the urban planning community typically encompass four steps [1]:

1. Trip generation modelling, forecasting the number of outbound trips from a location in light of current trip volumes and projected demographic changes;
2. Trip distribution modelling, estimating where trips originating in each zone will go to;
3. Mode choice, examining whether trips would be by mass transit, automobile or other;
4. Traffic assignment, allocating each trip to the most likely route.

Figure 1: Second Avenue Subway

By dividing the transport modelling process into four sequential stages, and examining the city as a number of individual Transport Analysis Zones (TAZs), such models are easy to use and indeed have been employed since the 1950s. Indeed, the Second Avenue Subway was itself evaluated based on a Transport Demand Forecasting Model (TDFM) that follows similar principles [2]. However, scholars increasingly see considerable potential for big-data approaches to supplement and improve upon transport demand modelling [3].

The TDFM employed by New York's Metropolitan Transit Authority (MTA) used turnstile swipe data, as well as future projections of housing, employment and population growth to project transport patterns with and without the Second Avenue extension. Built upon GIS and CAD software, it is a sophisticated system that encompasses the broader New York City area including trips originating from distant suburbs and New Jersey. Nevertheless, reviewing the methodology utilized for the Second Avenue Subway project appraisal reveals that it used relatively low-resolution data as part of the modelling [2]. Journeys to work (a key variable for subway demand) are modeling at the census tract level, and rely on census data.

Given the cost of a project such as the Second Avenue Subway, which cost around $4.5 billion, there is growing interest in improved methods to estimate future demand and evaluate whether such projects delivered the anticipated mobility benefits, moving beyond conventional (and still widely used) data sources such as travel diaries and census questions.

Call Detail Records have recently been used to construct Origin-Destination matrices for urban mass transit [4]. However, availability of CDR data is constrained by privacy concerns, which may hamper the uptake of this approach. Smart card data offers another avenue for research, exemplified by studies in Rotterdam and Singapore that impute home and work locations for individuals, and use agent-based modelling to generate macro-scale transport predictions [5,6]. However, New York lacks a 'touch-in, touch-out' card system.

In the New York context, an alternative is presented by taxi data, which is available at high spatial resolution for every trip on the city's yellow and green cabs. New York University's Rudin Center for Transportation Policy has conducted an analysis of taxi pick-ups and drop-offs in the Upper East Side for one week after the subway stations opened, finding a drop usage [7]. The study confirms the viability of using taxi demand to impute changes in transport demand patterns, and it suggests several variables to investigate further: such as distance to nearest subway station, and effect of weather on trip demand. Several interesting questions arise which were not addressed in the Rudin study, such as how travel patterns between different neighborhood pairs across the city were affected.

In conclusion, the existing literature suggests considerable scope to use large, passively collected datasets such as taxi pick-ups and drop-offs to supplement and enrich existing travel demand modelling. Taxi data can help us draw conclusions about future transport demand - which is useful given planning decisions on building more Second Avenue Subway stations further north into Harlem - and help us evaluate how the subways affected mobility for different groups of New Yorkers.

2. Data and approach

Table 1 Data Type and Source Location

Data type	Notes and source location
TLC Trip Record Data	Variables of interest include pick-up time, drop-off time, trip distance, longitude, and latitude. Data is high spatial and temporal resolution. http://www.nyc.gov/html/tlc/html/about/trip_record_data.shtml
Shapefiles	Boundaries for the TLC taxi zones: https://s3.amazonaws.com/nyc-tlc/misc/taxi_zones.zip Subway lines: https://data.cityofnewyork.us/Transportation/Subway-Lines/3qz8-muuu

Data from the TLC's trip records was utilized together with shapefiles for the relevant TLC Taxi Zones. Python was used for data cleaning and time series decomposition. R was used to conduct the cluster analysis. ArcGIS was used for visualising descriptive statistics and clustering results.

3. Exploratory Data Analysis

Data cleaning

The study utilized taxi trip recorded for New York City's yellow and green taxis for one month before the subway stations opened (April 2016) and one month after they opened (April 2017). The data were downloaded from the Taxi and Limousine Commission (TLC) website.

The TLC previously made taxi trip records available at precise X,Y geolocations. Due to privacy concerns, this practice was ended in 2017 with pick-up and drop-off locations instead aggregated at the level of TLC taxi zones. Data cleaning was therefore required to make the 2016 and 2017 datasets comparable. To accomplish this, we aggregated the April 2016 dataset and added a location ID corresponding to the TLC taxi zones, using the shapefile for these zones acquired from the TLC website.

Dataset for treatment and control areas

We selected treatment and control areas designed to model the impact of the new subway stations on mobility patterns. The treatment area was Lenox Hill East and Yorkville East (TLC location IDs: 140, 141, 262 and 263). This area was chosen as it represents the part of the city closest to the new subway stations and which was historically underserved by public transport.

We considered several potential control areas out of districts with similar demographic characteristics that did not see a change in transport availability during the period in question. Having evaluated options including Chelsea and Midtown East, we settled upon the Sutton Place / Turtle Bay North area (TLC ID: 299), which had the closest demographic and land use characteristics compared to our control.

Several steps were required to produce the dataset:

- For inbound trips, we filtered the data and only kept trip records with drop-off locations within these two areas.
- The dataset was then aggregated by location ID and pick-up date. We thereby obtained a time series of daily to Upper East and Sutton Place for each TLC ID.
- A similar approach was performed for outbound trips from the two areas.
- The yellow and green taxi trip record numbers were combined and the dataset of 2016 and 2017 was stacked.
- Finally a matrix for inbound and outbound trips, corresponding to the 263 TLC zone IDs and 56 days, was developed for both the treatment and control groups.

Visual inspection of trip data

	Number of outbound journeys from UES treatment zone, April 2016	Number of outbound journeys from UES treatment zone, April 2017	Percentage change
Upper East Side North	106,227	70,011	-34.1%
Upper East Side South	90,894	50,386	-44.6%
Midtown East	53,130	30,181	-43.2%
Midtown Center	41,434	21,438	-48.3%
East Harlem South	36,841	23,871	-35.2%

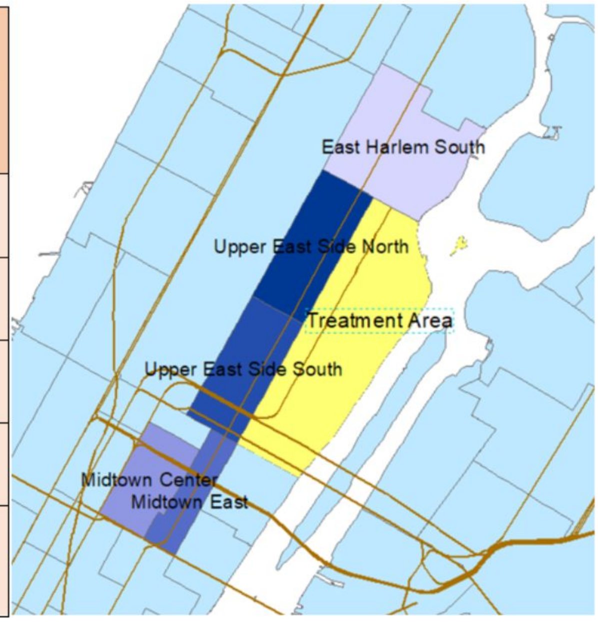

Figure 2.Top 5 Destination Area of Outbound Journeys from UES Treatment Areas in April 2016

In figure 2, we firstly illustrated the top 5 Destination Area of Outbound Journeys from UES Treatment Areas in April 2016, and their percentage of declination to April 2017. The difference in trip numbers between April 2016 and April 2017 is illustrated in Figure 3. These maps highlight the city locations from which inbound trips declined most after the subway stations opened - with the control area seeing little year-on-year change but the treatment area, as expected given the new subway line, seeing considerable change in inbound taxi journeys.

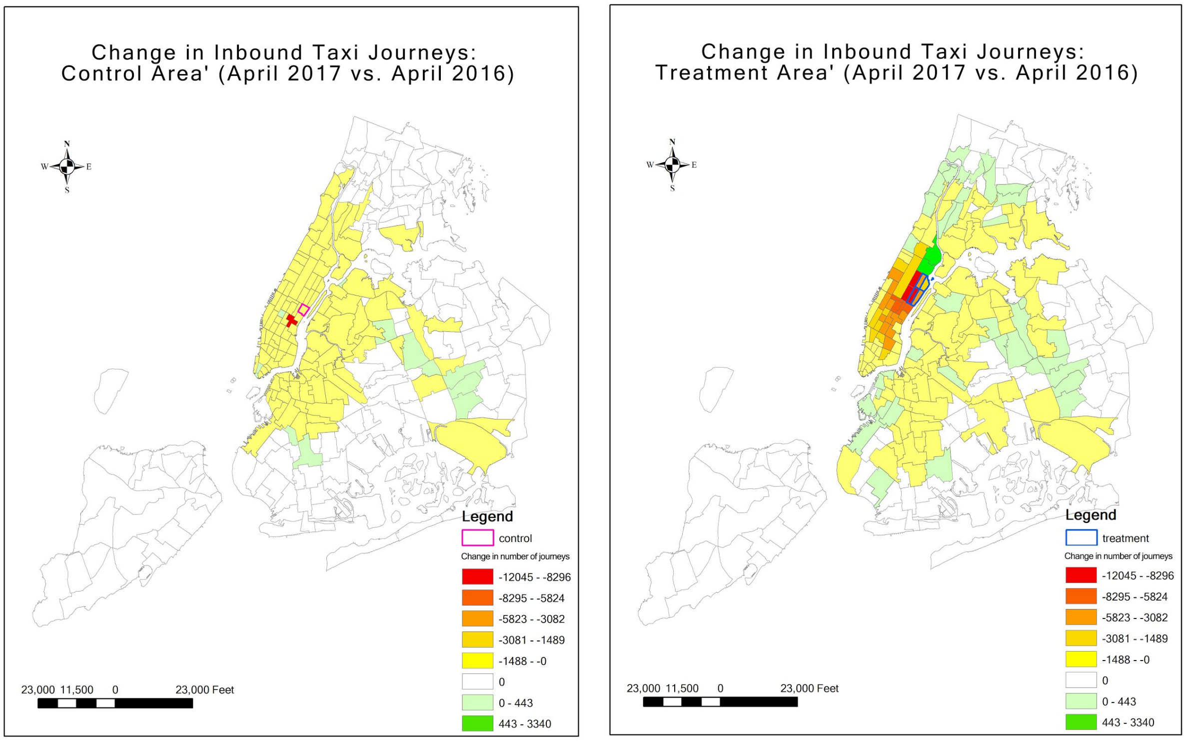

Figure 3.Change in Inbound Taxi Journeys in Treatment / Control Areas

For the two maps in Figure 4, the range represented by each color is the same, therefore the color ramp clearly illustrates changes in transport patterns. From April 2016 to April 2017, the number of inbound taxis generally declines. This is not surprising in the context of rising Uber usage. Compared to the treatment group, we see a significant decline in number of people who took a taxi to the area from Midtown, from parts of the Upper West Side, and from other Upper East Side locations.

Interestingly, the number of people who take a taxi to the treatment area from East Harlem sees an increase of between 115-110 people per day. We hypothesize that this may be due to (i) East Harlem residents taking taxis to the Upper East Side then changing onto the new subway line to get to other locations; and (ii) increased attractiveness of the neighborhood as a leisure destination.

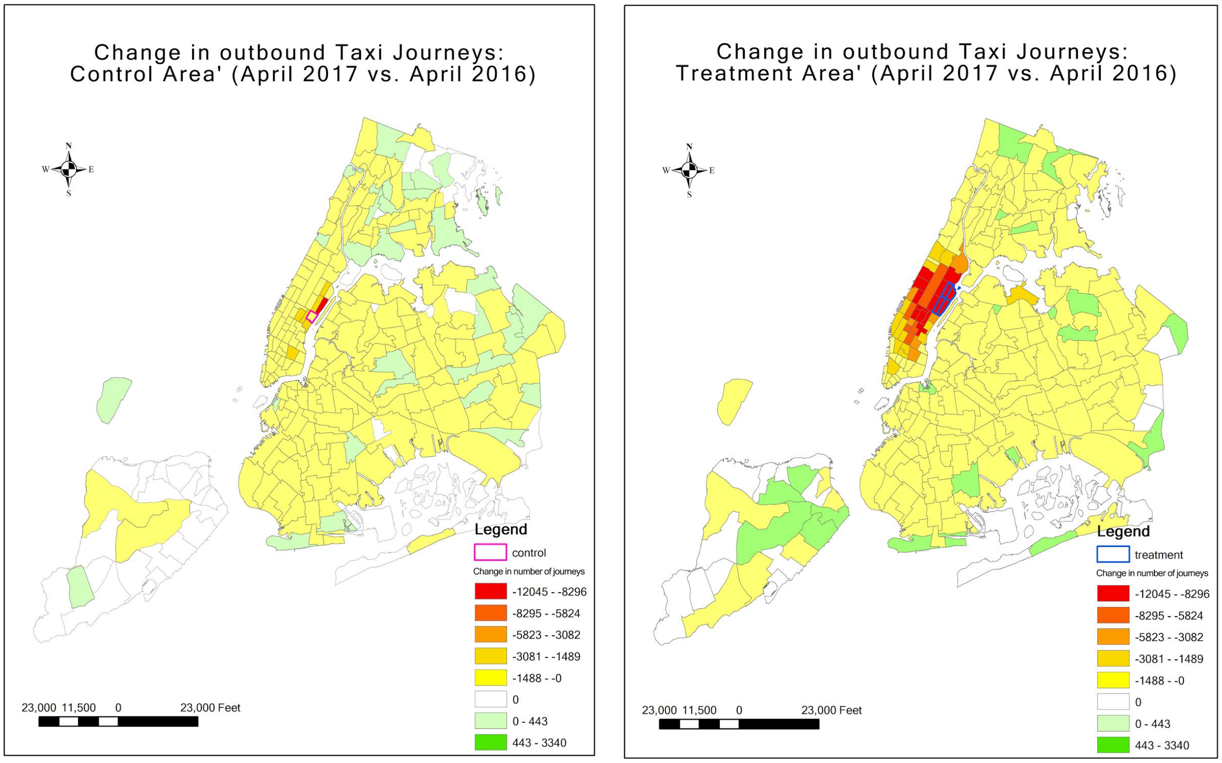

Figure 4. Change in Outbound Taxi Journeys in Treatment / Control Areas

Subway connectivity has led to a significant reduction in the number of people traveling from the treatment zone to nearby areas, especially in Midtown.

Table 2 : Origins for Incoming Journeys By Largest Percent Change

To UES treatment area (rides increased)		To Sutton Place control area (rides increased)		To UES treatment area (rides decreased)		To Sutton Place control area (rides decreased)	
Washington Heights South	72.7%	Garment District	0.8%	Bedford	-94.7%	East Harlem North	-44.7%
East Harlem North	42.6%	Decline in all other Control Area mildly		Mott Haven/ Port Morris	-90.8%	Sunnyside	-43.9%
East Harlem South	16.5%			Randall's Island	-82.5%	Stuy Town /Peter Cooper Village	-33.4%
Astoria	15.2%			Queensbridge /Ravenswood	-78.8%	East Harlem South	-32.4%
Williamsburg (North Side)	11.7%			East Williamsburg	-73.2%	Financial District North	-28.4%

Table 3 : Destinations for Outbound Journeys By Largest Percent Change

From UES treatment area (rides increased)	From Sutton Place control area (rides increased)	To UES treatment area (rides decreased)		To Sutton Place control area (rides decreased)	
Decline in all Treatment Area mildly	Decline in all Control Area mildly	Times Sq/Theatre District	-52.8%	East Harlem North	-37.5%
		Midtown North	-52.0%	Sunnyside	-36.3%
		Midtown South	-51.7%	Stuy Town/Peter Cooper Village	-29.8%
		Meatpacking/ West Village West	-50.6%	East Harlem South	-29.6%
		Garment District	-49.3%	Financial District North	-28.1%

4. Methodology

We are interested in how the mobility of the neighborhood was affected by the opening of the new subway stations (72 St, 86 St, 96 St). To understand this we investigate taxi pick-ups and drop-offs in the surrounding area. Using the geographic and time-series data available from the TLC, we are able to examine change in number outbound taxi trips by destination TLC location ID.

In order to examine the change of taxi rides after the opening of the new subway stations and categorise the neighborhoods with similar trends, hierarchical time series clustering analysis is performed. The time series analysis focuses on the outbound pick-ups from the Upper East Side.

4.1 Time series clustering

The taxi pick-up number time series are filled with fluctuations, trends and random noises, which increase the difficulty to categorise the neighbourhoods. In addition, the concerns of time series may vary according to different research goals. In this study, we are more interested in the trend components before and after the new subway stations opened. Thus, instead of clustering raw time series, decomposing time series into weekly, trend and random components is vital. Using centered moving averages, a time series Y[t] is decomposed using an additive model:

$$Y[t] = T[t] + S[t] + e[t]$$

where T[t] is trend component, S[t] is the seasonal component and e[t] is the remainder part. First, the trend component is derived using a moving average with time period of 7 days. Then the trend component is removed from the series. The seasonal component is the mean of each time unit over all periods. For this project, the seasonal component is calculated by averaging each Monday, Tuesday to Sunday's pick-up numbers after removing the trend component. The remainder part which is also the random component is obtained by removing the seasonal component and trend component from the original time series.

4.2. Trend clustering using correlation coefficient

The seasonal component shows the weekly fluctuation of an area's taxi pick-up numbers, while the trend component reveals the long-term trend of taxi pick-up numbers. When research the changes in long-term trend, it's better to remove the weekly fluctuation and only focus on the trend component. In this project, the pick-up trend is the trend component extracted from daily taxi pick-up time series, and is used to conduct a hierarchical cluster analysis. The trend analysis concerns about trend components' shape, not amount. Thus, correlation is considered as the dissimilarity measure. The correlation matrix map is shown in Figure 5. Since the distance for cluster analysis can not be negative, the dissimilarity is defined as:

Dissimilarity = 1 − Correlation

Then a hierarchical cluster analysis is conducted using the agglomeration method of "ward.D", which is derived from Ward's criterion. Ward method is inspired from ANOVA. Each cluster obtained according to Ward's criterion has the minimum sum of squares of deviations while the sum of squares of deviations between clusters reaches the largest. First, each observation is a cluster. Then for each iteration, the number of clusters decrease by 1, which is realised by combining two clusters that causes the minimum increasing of sum of squares of deviations. Finally, all clusters are reunited into 1 cluster. The dendrogram of clusters is shown in Figure 6.

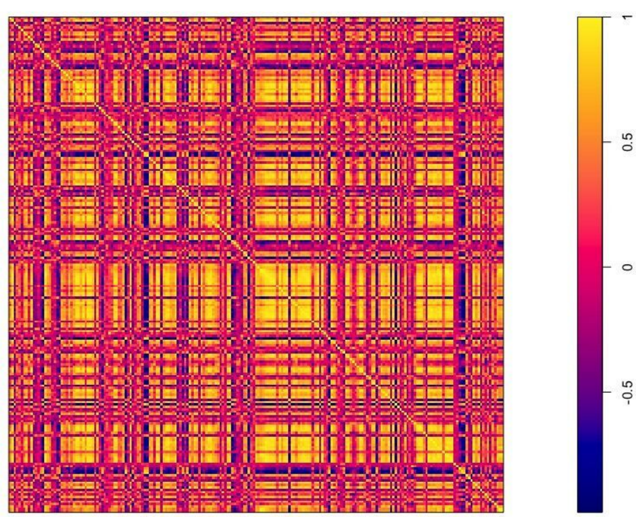

Figure 5. Correlation Matrix Map

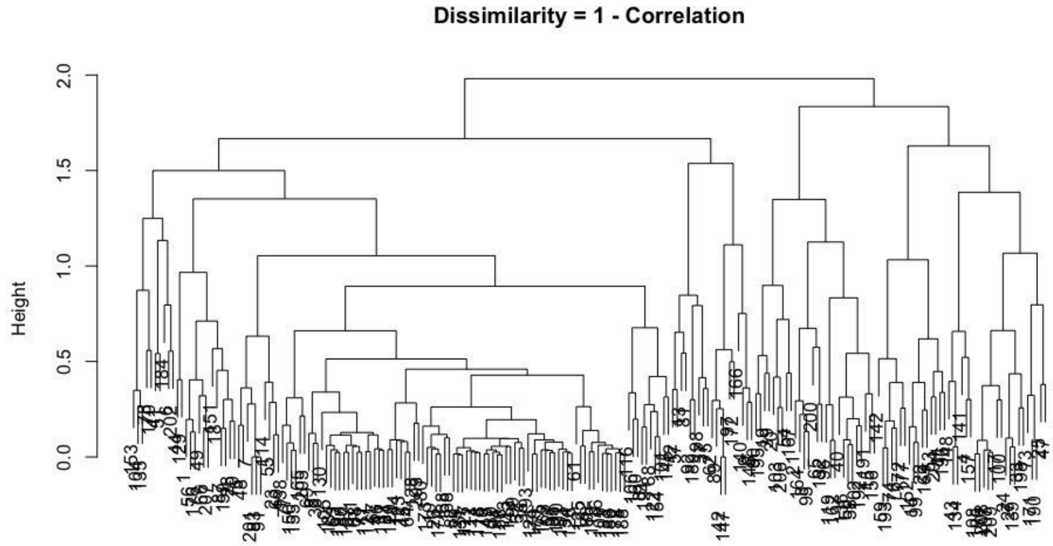

Figure 6. Dendrogram of taxi trips clusters (number represents TLC IDs)

5. Results and Discussion

For the outbound trips from the Upper East Side, the cluster analysis has grouped the 263 taxi zones into four clusters, based on the number of pick-ups either (i) decreasing to a stable level; (ii) decreasing to a fluctuating level; (iii) following a random pattern; or (iv) remaining zero. Table 3 shows the zones included in each cluster (*see appendix*). There are 7 taxi zones do not have taxi pick-ups all the time, which are categorised as remaining zero. The following plots show the trend of pick-ups for each cluster. The red dashed line is the boundary of April 2016 and April 2017.

__Cluster 1: Decrease to a stable level__

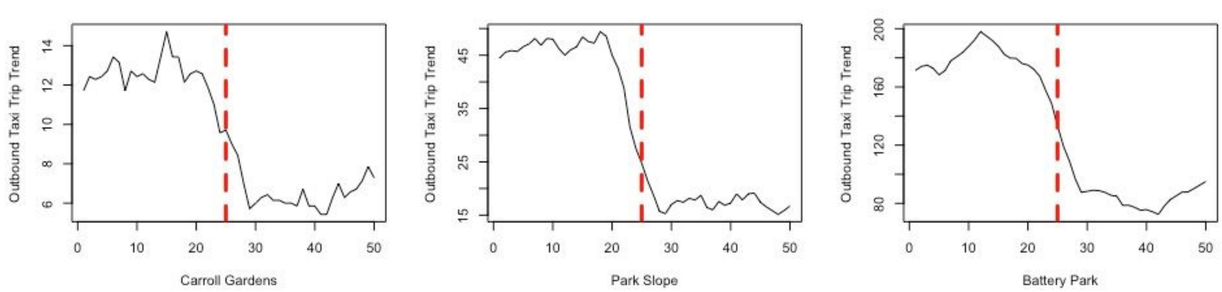

Figure 7. The Trend Components of Taxi Pick-up Time Series in April 2016 and April 2017 of Carroll Garden, Park Slope and Battery Park

There are 116 taxi zones grouped in the cluster which denotes the trend of taxi pick-ups decrease to a stable level. The taxi zones in this cluster, including the three depicted above, have a stable level of pick-up trend in April 2016 and decreased to a stable level in April 2017. The trends in April 2017 have smaller pick-ups numbers but the curve of the trend does not change drastically in 2017. For example, Battery Park's pick-up trends were around 90 in April 2017 but were around 180 in April 2016. In April 2016, the pick-up trends first increased to 200 then decreased to 160, however in April 2017, the pick-up trends were around 80 all the month. This means after the Second Avenue Subway is opened, a fixed number of commuters rely on taxi in 2016 no longer travel by taxi in 2017. In some areas like Battery Park, the fluctuation of taxi pick-up trends were eliminated in 2017.

Cluster 2: Decrease to a fluctuating level

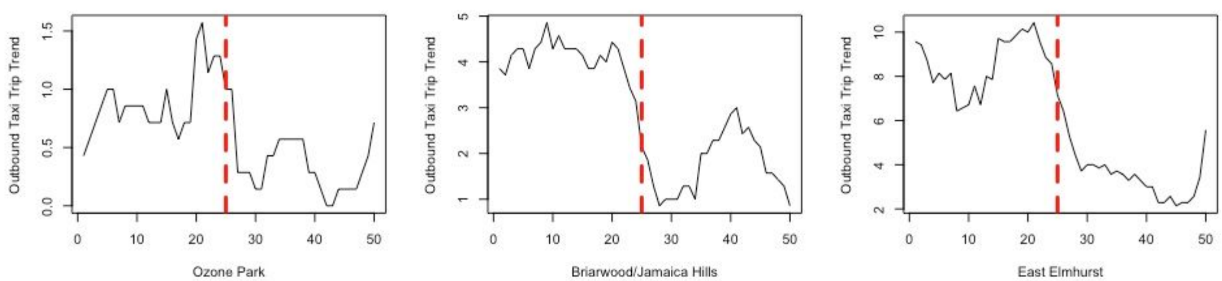

Figure 8. The Trend Components of Taxi Pick-up Time Series in April 2016 and April 2017 of Ozone Park, Briarwood/Jamaica and East Elmhurst

There are 61 taxi zones grouped in the cluster which denotes the trend of taxi pick-ups decrease to a fluctuating level. Comparing to the former cluster, this cluster shows the zones also having decreasing trends but with fluctuation in April 2017. This means after the Second Avenue Subway is opened, a number of people travel by taxi less but sometimes they will ride taxi again. The number of taxi pick-ups are eliminated to near zero.

Cluster 3: Random

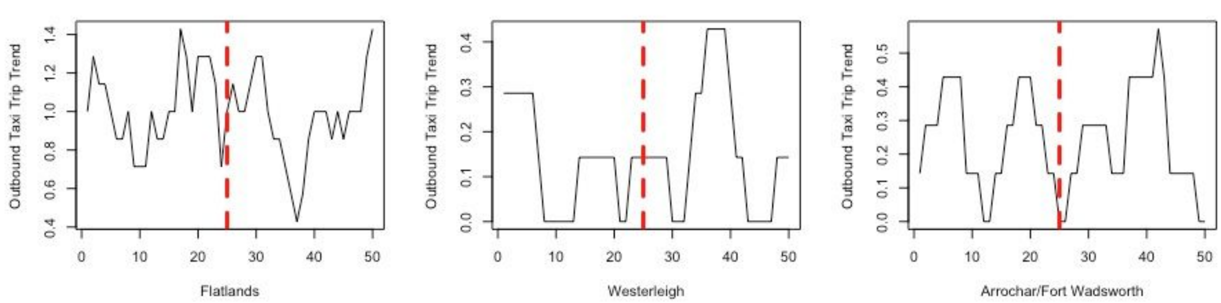

Figure 9. The Trend Components of Taxi Pick-up Time Series in April 2016 and April 2017 of Flatlands, Westerleigh and Arrochar/Fort Wadsworth

There are 79 taxi zones grouped in the cluster which denotes the trend of taxi pick-ups changes randomly. The zones in this cluster follow random trends. There are no obvious changes in patterns before and after the Second Avenue Subway is opened. These zones have smaller numbers of taxi trends closing to zero.

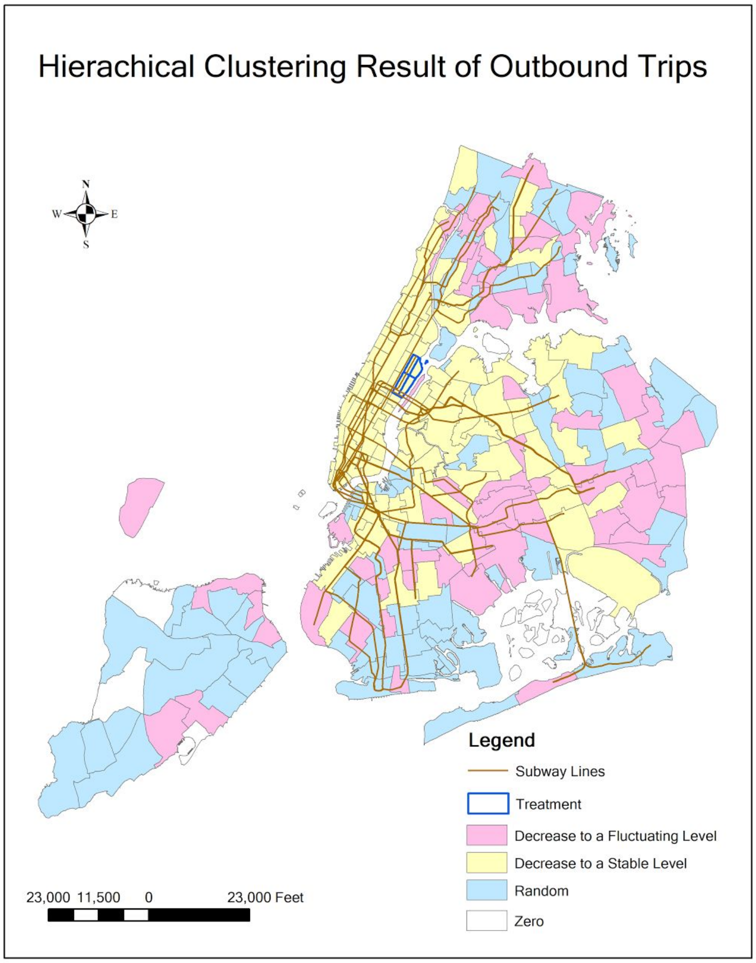

Figure 10 shows the spatial relation for the cluster results. The taxi zones following the decrease-then-stable pattern locate mainly in Manhattan, zones in the Bronx, Queens and Brooklyn near Manhattan and zones near airports. The decrease-then-stable zones are highly overlapped with the districts passed by subway lines. The zones following decrease-then-fluctuating pattern mainly located away from Manhattan, while the zones follow random pattern locating mainly on the border of New York City.

Figure 10. The Cluster Result Map for New York City Taxi Zones

6. Limitations and extensions

The analysis only included dataset of April 2016 and April 2017. The main reason of eliminating the study of one month is that as mentioned above, TLC stopped including precise X,Y geolocations in trip records since 2017 considering privacy issues. The aggregation process using polygons of TLC zones is highly time-consuming and computationally expensive. For future work, more observations from January to June of 2016 and 2017 can be included in analysis.

In future work, more factors such as weather condition, distance of pick-up locations to subway entrances, and trip duration can be added to research on the influence on neighborhood mobility after the newly opened subway stations.

7. Conclusion

The project analyzed taxi usage trends to and from two areas: the Yorkville and Lenox Hill areas of the Upper East Side (treatment group - benefiting from the new subway stations) and Sutton Place / Turtle Bay East (control group (not affecting by new subway stations). We compared taxi pick-ups and drop-offs in April 2017 compared with April 2016. The analysis shows significant changes in taxi usage numbers after the subway stations opened. Areas with a direct subway link, such as East Williamsburg, saw decreases in outward taxi journeys of 60% of more (April 2017 vis-a-vis April 2016) in some cases. While the control group also saw a general decline in taxi journeys (inbound and outbound), which may be attributable to rising Uber usage at this time, the treatment group sees large and significant decreases in taxi usage at the time the new subway stations came online. Interestingly, the change in taxi usage differs by origin and destination neighborhood, as revealed by the clustering analysis.

Through a clustering analysis using time series data for destination neighborhoods, we identify neighborhood that saw a pronounced and clear change in transport patterns following the new subway stations. Districts in outer Borough locations such as Staten Island and further parts of Queens saw no discernible pattern of change in the cluster analysis, as expected given the low two-way taxi and subway traffic between them. By contrast, Financial District North, Flatiron, Carroll Gardens and Park Slope are among areas that saw a decrease followed by stable usage pattern, while others saw a decrease following by fluctuation in usage. The Second Avenue Subway, we conclude, resulted in immediately discernible changes in taxi usage as customers moved from taxi to public transit where the new line facilitated this switch. The time series clustering method developed here can be employed in a number of use cases, such as evaluating whether a new line improved mobility for neighborhoods across the city, calculating the propensity of customers to switch between modes of transport based on availability of new lines, and ground-truthing the transport demand calculations produced through standards four-stage models.

References

[1] **De Dios Ortuzar, Juan and Luis G. Williamson**. 2011. *Transport Modelling.* 4th edition. London: Wiley.

[2] **Metropolitan Transport Authority.** 2001. *Supplemental Draft Environmental Impact Statement on the Manhattan East Site Alternatives Project - "Second Avenue Subway."* Accessed online: www.gpo.gov/fdsys/granule/FR-2001-03-22/01-7070

[3] **Cuauhtemoc Anda, Alexander Erath & Pieter Jacobus Fourie**. 2017. 'Transport modelling in the age of big data', International Journal of Urban Sciences, Vol. 21, Iss. sup 1.

[4] **Toole, J.L., et al.** 2015. *The path most traveled: Travel demand estimation using big data resources*. Transport. Res. Part C, http://dx.doi.org/10.1016/j.trc.2015.04.022

[5] **Bouman, P., E. Van der Hurk, L. Kroon, T. Li and P. Vervest**. 2013. *Detecting activity patterns from smart card Data*. Paper presented at the BNAIC 2013: Proceedings of the 25th Benelux Conference on Artificial Intelligence, Delft, The Netherlands, November 7-8, 2013.

[6] **Chakirov, A. and A. Erath**. 2012. *Activity Identification and Primary Location Modelling based on Smart Card Payment Data for Public Transport*. International Conference on Travel Behaviour Research (IATBR), Toronto, June 2012.

[7] **Kaufman, Sarah M. and Ari L. Kaputkin**. Not dated. *Upper East Side Taxis and the Second Avenue Subway.* New York University Rudin Center for Transportation. Accessed online: https://wagner.nyu.edu/files/faculty/publications/SASandTaxis.pdf

Appendix: Clustering Analysis

The table below shows the results of a clustering analysis of outbound trips from the Upper East Side to other taxi zones across the city. Taxi zones were clustered into four groups based on their change in taxi ride numbers to the treatment zone in April 2017 compared with April 2016.

Table 3: Clustering Analysis of Outbound Trips from Upper East Side (treatment area)

Taxi zone	Borough	Status
Allerton/Pelham Gardens	Bronx	Decrease to a fluctuating level
Bedford Park	Bronx	Decrease to a fluctuating level
Belmont	Bronx	Decrease to a stable level
Bronx Park	Bronx	Random
Bronxdale	Bronx	Decrease to a stable level
City Island	Bronx	Random
Claremont/Bathgate	Bronx	Decrease to a fluctuating level
Co-Op City	Bronx	Random
Country Club	Bronx	Random
Crotona Park	Bronx	Random
Crotona Park East	Bronx	Decrease to a fluctuating level
East Concourse/Concourse Village	Bronx	Decrease to a stable level
East Tremont	Bronx	Decrease to a fluctuating level
Eastchester	Bronx	Random
Fordham South	Bronx	Random
Highbridge	Bronx	Decrease to a stable level
Hunts Point	Bronx	Decrease to a fluctuating level
Kingsbridge Heights	Bronx	Decrease to a fluctuating level

Longwood	Bronx	Random
Melrose South	Bronx	Decrease to a stable level
Morrisania/Melrose	Bronx	Decrease to a fluctuating level
Mott Haven/Port Morris	Bronx	Decrease to a stable level
Mount Hope	Bronx	Decrease to a fluctuating level
Norwood	Bronx	Random
Parkchester	Bronx	Random
Pelham Bay	Bronx	Random
Pelham Bay Park	Bronx	Decrease to a fluctuating level
Pelham Parkway	Bronx	Decrease to a fluctuating level
Rikers Island	Bronx	zero
Riverdale/North Riverdale/Fieldston	Bronx	Decrease to a stable level
Schuylerville/Edgewater Park	Bronx	Decrease to a fluctuating level
Soundview/Bruckner	Bronx	Random
Soundview/Castle Hill	Bronx	Decrease to a fluctuating level
Spuyten Duyvil/Kingsbridge	Bronx	Random
University Heights/Morris Heights	Bronx	Random
Van Cortlandt Park	Bronx	Random
Van Cortlandt Village	Bronx	Decrease to a fluctuating level
Van Nest/Morris Park	Bronx	Decrease to a stable level
West Concourse	Bronx	Random
West Farms/Bronx River	Bronx	Random
Westchester Village/Unionport	Bronx	Random
Williamsbridge/Olinville	Bronx	Decrease to a stable level
Woodlawn/Wakefield	Bronx	Decrease to a fluctuating level
Bath Beach	Brooklyn	Random
Bay Ridge	Brooklyn	Decrease to a fluctuating level
Bedford	Brooklyn	Decrease to a stable level
Bensonhurst East	Brooklyn	Random
Bensonhurst West	Brooklyn	Decrease to a fluctuating level
Boerum Hill	Brooklyn	Decrease to a stable level
Borough Park	Brooklyn	Random
Brighton Beach	Brooklyn	Decrease to a fluctuating level
Brooklyn Heights	Brooklyn	Random
Brooklyn Navy Yard	Brooklyn	Random
Brownsville	Brooklyn	Decrease to a stable level
Bushwick North	Brooklyn	Decrease to a fluctuating level
Bushwick South	Brooklyn	Decrease to a stable level
Canarsie	Brooklyn	Decrease to a fluctuating level
Carroll Gardens	Brooklyn	Decrease to a stable level
Clinton Hill	Brooklyn	Decrease to a stable level
Cobble Hill	Brooklyn	Random
Columbia Street	Brooklyn	Random

Coney Island	Brooklyn	Random
Crown Heights North	Brooklyn	Random
Crown Heights South	Brooklyn	Random
Cypress Hills	Brooklyn	Decrease to a fluctuating level
Downtown Brooklyn/MetroTech	Brooklyn	Decrease to a stable level
DUMBO/Vinegar Hill	Brooklyn	Decrease to a stable level
Dyker Heights	Brooklyn	Decrease to a stable level
East Flatbush/Farragut	Brooklyn	Decrease to a stable level
East Flatbush/Remsen Village	Brooklyn	Decrease to a fluctuating level
East New York	Brooklyn	Decrease to a fluctuating level
East New York/Pennsylvania Avenue	Brooklyn	Decrease to a fluctuating level
East Williamsburg	Brooklyn	Decrease to a stable level
Erasmus	Brooklyn	Decrease to a fluctuating level
Flatbush/Ditmas Park	Brooklyn	Decrease to a stable level
Flatlands	Brooklyn	Random
Fort Greene	Brooklyn	Decrease to a stable level
Gowanus	Brooklyn	Decrease to a stable level
Gravesend	Brooklyn	Random
Green-Wood Cemetery	Brooklyn	Decrease to a fluctuating level
Greenpoint	Brooklyn	Decrease to a stable level
Homecrest	Brooklyn	Random
Kensington	Brooklyn	Decrease to a fluctuating level
Madison	Brooklyn	Random
Manhattan Beach	Brooklyn	Random
Marine Park/Floyd Bennett Field	Brooklyn	Random
Marine Park/Mill Basin	Brooklyn	Random
Midwood	Brooklyn	Random
Ocean Hill	Brooklyn	Random
Ocean Parkway South	Brooklyn	Decrease to a fluctuating level
Park Slope	Brooklyn	Decrease to a stable level
Prospect-Lefferts Gardens	Brooklyn	Decrease to a fluctuating level
Prospect Heights	Brooklyn	Decrease to a stable level
Prospect Park	Brooklyn	Decrease to a fluctuating level
Red Hook	Brooklyn	Decrease to a fluctuating level
Sheepshead Bay	Brooklyn	Random
South Williamsburg	Brooklyn	Random
Starrett City	Brooklyn	Random
Stuyvesant Heights	Brooklyn	Decrease to a fluctuating level
Sunset Park East	Brooklyn	Random
Sunset Park West	Brooklyn	Decrease to a stable level
Williamsburg (North Side)	Brooklyn	Decrease to a stable level
Williamsburg (South Side)	Brooklyn	Random
Windsor Terrace	Brooklyn	Random

Newark Airport	EWR	Decrease to a fluctuating level
Alphabet City	Manhattan	Decrease to a stable level
Battery Park	Manhattan	Decrease to a stable level
Battery Park City	Manhattan	Decrease to a stable level
Bloomingdale	Manhattan	Decrease to a stable level
Central Harlem	Manhattan	Decrease to a stable level
Central Harlem North	Manhattan	Decrease to a stable level
Central Park	Manhattan	Decrease to a stable level
Chinatown	Manhattan	Decrease to a stable level
Clinton East	Manhattan	Decrease to a stable level
Clinton West	Manhattan	Decrease to a stable level
East Chelsea	Manhattan	Decrease to a stable level
East Harlem North	Manhattan	Decrease to a stable level
East Harlem South	Manhattan	Decrease to a stable level
East Village	Manhattan	Decrease to a stable level
Financial District North	Manhattan	Decrease to a stable level
Financial District South	Manhattan	Decrease to a stable level
Flatiron	Manhattan	Decrease to a stable level
Garment District	Manhattan	Decrease to a stable level
Governor's Island/Ellis Island/Liberty Island	Manhattan	zero
Governor's Island/Ellis Island/Liberty Island	Manhattan	zero
Governor's Island/Ellis Island/Liberty Island	Manhattan	zero
Gramercy	Manhattan	Decrease to a stable level
Greenwich Village North	Manhattan	Decrease to a stable level
Greenwich Village South	Manhattan	Decrease to a stable level
Hamilton Heights	Manhattan	Decrease to a stable level
Highbridge Park	Manhattan	Decrease to a fluctuating level
Hudson Sq	Manhattan	Decrease to a stable level
Inwood	Manhattan	Decrease to a fluctuating level
Inwood Hill Park	Manhattan	Decrease to a stable level
Kips Bay	Manhattan	Decrease to a stable level
Lenox Hill East	Manhattan	Decrease to a stable level
Lenox Hill West	Manhattan	Decrease to a stable level
Lincoln Square East	Manhattan	Decrease to a stable level
Lincoln Square West	Manhattan	Decrease to a stable level
Little Italy/NoLiTa	Manhattan	Decrease to a stable level
Lower East Side	Manhattan	Decrease to a stable level
Manhattan Valley	Manhattan	Decrease to a stable level
Manhattanville	Manhattan	Decrease to a stable level
Marble Hill	Manhattan	Decrease to a fluctuating level
Meatpacking/West Village West	Manhattan	Decrease to a stable level
Midtown Center	Manhattan	Decrease to a stable level
Midtown East	Manhattan	Decrease to a stable level

Midtown North	Manhattan	Decrease to a stable level
Midtown South	Manhattan	Decrease to a stable level
Morningside Heights	Manhattan	Decrease to a stable level
Murray Hill	Manhattan	Decrease to a stable level
Penn Station/Madison Sq West	Manhattan	Decrease to a stable level
Randalls Island	Manhattan	Random
Roosevelt Island	Manhattan	Decrease to a fluctuating level
Seaport	Manhattan	Decrease to a stable level
SoHo	Manhattan	Decrease to a stable level
Stuy Town/Peter Cooper Village	Manhattan	Decrease to a stable level
Sutton Place/Turtle Bay North	Manhattan	Decrease to a stable level
Times Sq/Theatre District	Manhattan	Decrease to a stable level
TriBeCa/Civic Center	Manhattan	Decrease to a stable level
Two Bridges/Seward Park	Manhattan	Decrease to a stable level
UN/Turtle Bay South	Manhattan	Decrease to a stable level
Union Sq	Manhattan	Decrease to a stable level
Upper East Side North	Manhattan	Decrease to a stable level
Upper East Side South	Manhattan	Decrease to a stable level
Upper West Side North	Manhattan	Decrease to a stable level
Upper West Side South	Manhattan	Decrease to a stable level
Washington Heights North	Manhattan	Decrease to a stable level
Washington Heights South	Manhattan	Decrease to a stable level
West Chelsea/Hudson Yards	Manhattan	Decrease to a stable level
West Village	Manhattan	Decrease to a stable level
World Trade Center	Manhattan	Decrease to a stable level
Yorkville East	Manhattan	Decrease to a stable level
Yorkville West	Manhattan	Decrease to a stable level
Jamaica Bay	Queens	zero
Astoria	Queens	Decrease to a stable level
Astoria Park	Queens	Random
Auburndale	Queens	Random
Baisley Park	Queens	Decrease to a fluctuating level
Bay Terrace/Fort Totten	Queens	Random
Bayside	Queens	Decrease to a fluctuating level
Bellerose	Queens	Decrease to a fluctuating level
Breezy Point/Fort Tilden/Riis Beach	Queens	Random
Briarwood/Jamaica Hills	Queens	Decrease to a fluctuating level
Broad Channel	Queens	Random
Cambria Heights	Queens	Decrease to a fluctuating level
College Point	Queens	Decrease to a stable level
Corona	Queens	Decrease to a stable level
Corona	Queens	Decrease to a stable level
Douglaston	Queens	Random

East Elmhurst	Queens	Decrease to a fluctuating level
East Flushing	Queens	Random
Elmhurst	Queens	Decrease to a stable level
Elmhurst/Maspeth	Queens	Decrease to a stable level
Far Rockaway	Queens	Random
Flushing	Queens	Decrease to a stable level
Flushing Meadows-Corona Park	Queens	Random
Forest Hills	Queens	Decrease to a stable level
Forest Park/Highland Park	Queens	Decrease to a fluctuating level
Fresh Meadows	Queens	Decrease to a stable level
Glen Oaks	Queens	Random
Glendale	Queens	Decrease to a fluctuating level
Hammels/Arverne	Queens	Random
Hillcrest/Pomonok	Queens	Random
Hollis	Queens	Decrease to a fluctuating level
Howard Beach	Queens	Random
Jackson Heights	Queens	Decrease to a stable level
Jamaica	Queens	Decrease to a fluctuating level
Jamaica Estates	Queens	Random
JFK Airport	Queens	Decrease to a stable level
Kew Gardens	Queens	Decrease to a stable level
Kew Gardens Hills	Queens	Decrease to a stable level
LaGuardia Airport	Queens	Decrease to a stable level
Laurelton	Queens	Random
Long Island City/Hunters Point	Queens	Decrease to a stable level
Long Island City/Queens Plaza	Queens	Decrease to a stable level
Maspeth	Queens	Random
Middle Village	Queens	Decrease to a stable level
Murray Hill-Queens	Queens	Random
North Corona	Queens	Decrease to a stable level
Oakland Gardens	Queens	Decrease to a fluctuating level
Old Astoria	Queens	Decrease to a stable level
Ozone Park	Queens	Decrease to a fluctuating level
Queens Village	Queens	Decrease to a fluctuating level
Queensboro Hill	Queens	Decrease to a fluctuating level
Queensbridge/Ravenswood	Queens	Decrease to a stable level
Rego Park	Queens	Decrease to a fluctuating level
Richmond Hill	Queens	Decrease to a stable level
Ridgewood	Queens	Decrease to a stable level
Rockaway Park	Queens	Decrease to a fluctuating level
Rosedale	Queens	Random
Saint Albans	Queens	Decrease to a fluctuating level
Saint Michaels Cemetery/Woodside	Queens	Random

South Jamaica	Queens	Decrease to a stable level
South Ozone Park	Queens	Decrease to a stable level
Springfield Gardens North	Queens	Decrease to a fluctuating level
Springfield Gardens South	Queens	Decrease to a fluctuating level
Steinway	Queens	Decrease to a stable level
Sunnyside	Queens	Decrease to a stable level
Whitestone	Queens	Decrease to a stable level
Willets Point	Queens	Random
Woodhaven	Queens	Decrease to a fluctuating level
Woodside	Queens	Decrease to a stable level
Arden Heights	Staten Island	Random
Arrochar/Fort Wadsworth	Staten Island	Random
Bloomfield/Emerson Hill	Staten Island	Random
Charleston/Tottenville	Staten Island	Random
Eltingville/Annadale/Prince's Bay	Staten Island	Random
Freshkills Park	Staten Island	zero
Great Kills	Staten Island	Decrease to a fluctuating level
Great Kills Park	Staten Island	zero
Grymes Hill/Clifton	Staten Island	Random
Heartland Village/Todt Hill	Staten Island	Random
Mariners Harbor	Staten Island	zero
New Dorp/Midland Beach	Staten Island	Random
Oakwood	Staten Island	Decrease to a fluctuating level
Port Richmond	Staten Island	Random
Rossville/Woodrow	Staten Island	Random
Saint George/New Brighton	Staten Island	Decrease to a fluctuating level
South Beach/Dongan Hills	Staten Island	Random
Stapleton	Staten Island	Decrease to a fluctuating level
West Brighton	Staten Island	Random
Westerleigh	Staten Island	Random