DID TAXI USAGE CHANGE AFTER THE SECOND AVENUE SUBWAY OPENED?
- A CLUSTERING ANALYSIS BASED ON TIME SERIES DATA

Applied Data Science Project

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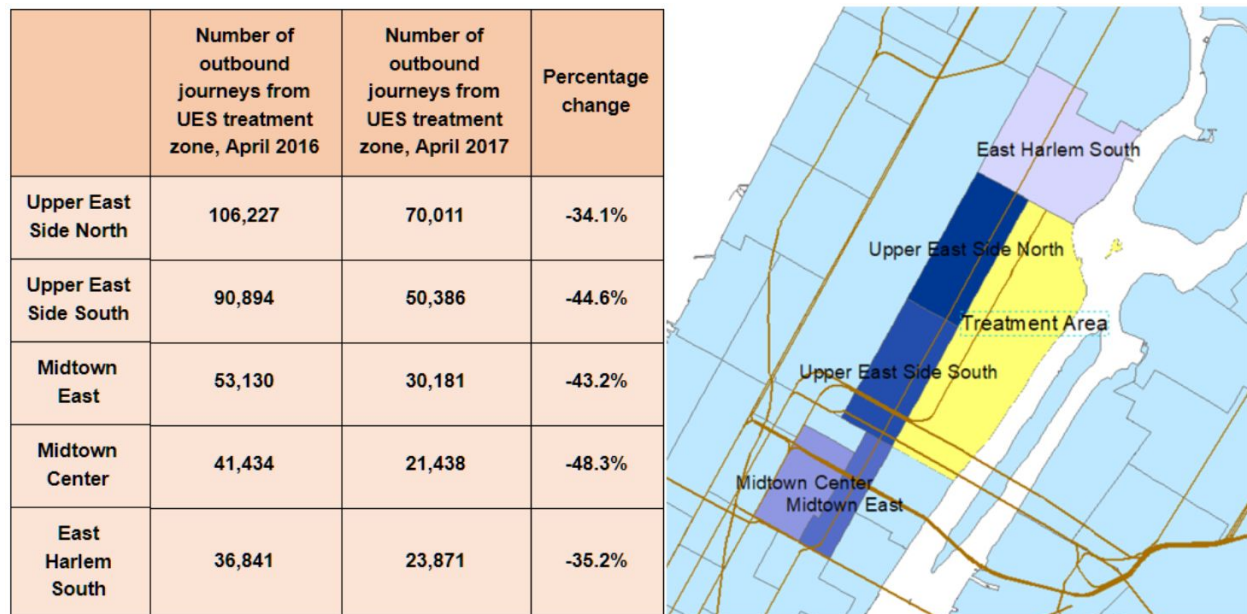
Figure 2.Top 5 Destination Area of Outbound Journeys from UES Treatment Areas in April 2016

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.

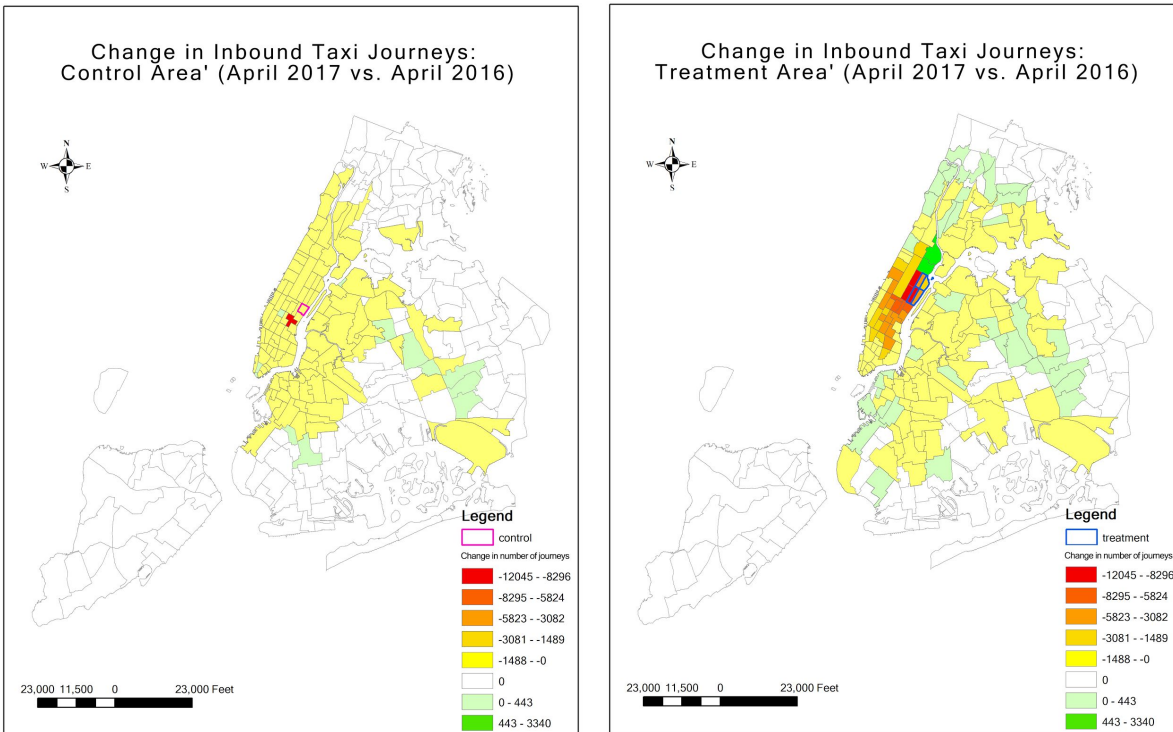**Figure 3.Change in Inbound Taxi Journeys in Treatment / Control Areas**

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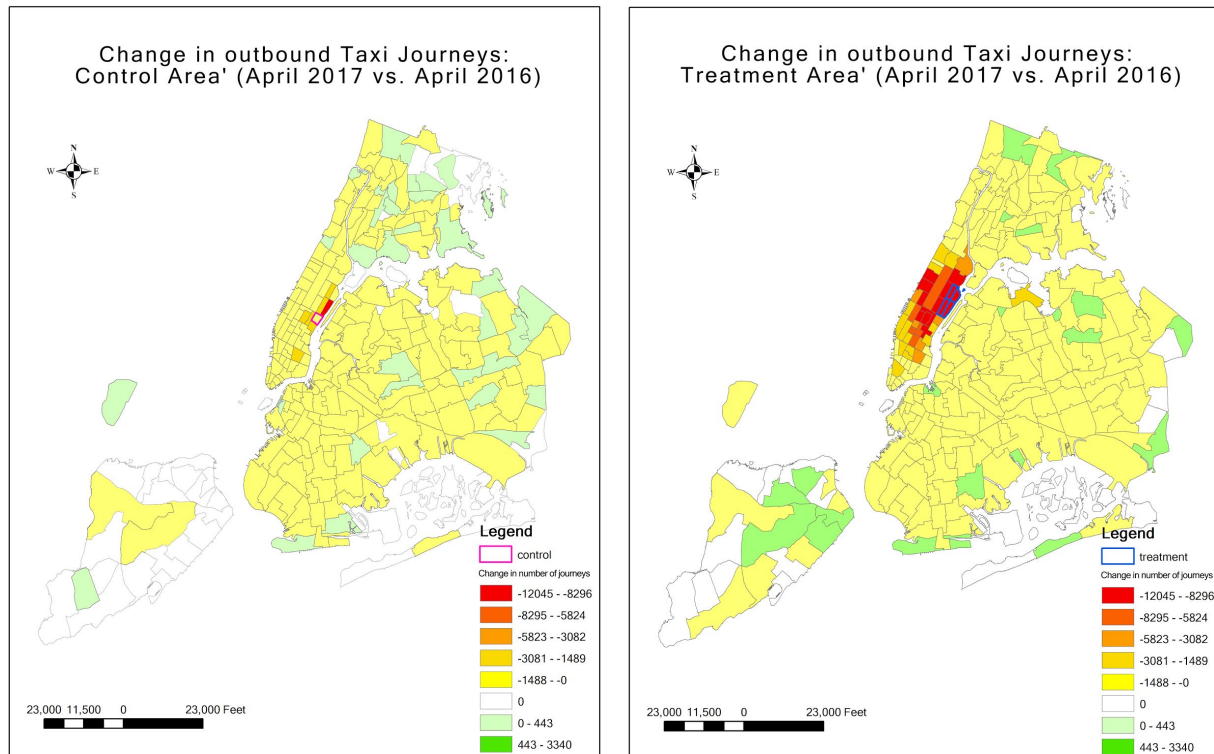
Figure 4. Change in Outbound Taxi Journeys in Treatment / Control Areas

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)		From UES treatment area (rides decreased)		From 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.
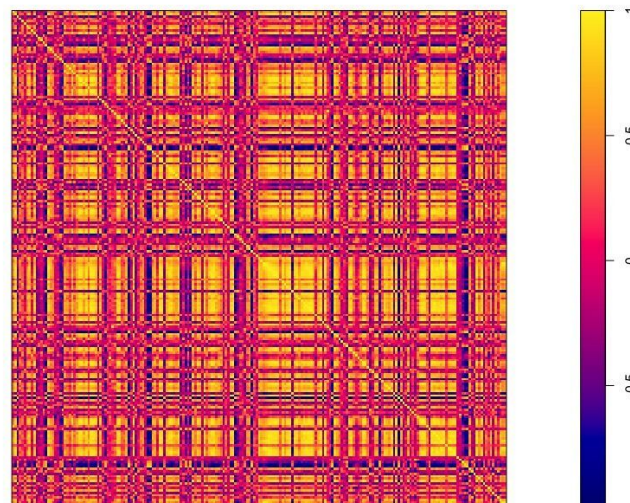
Figure 5. Correlation Matrix Map

Dissimilarity = 1 - Correlation
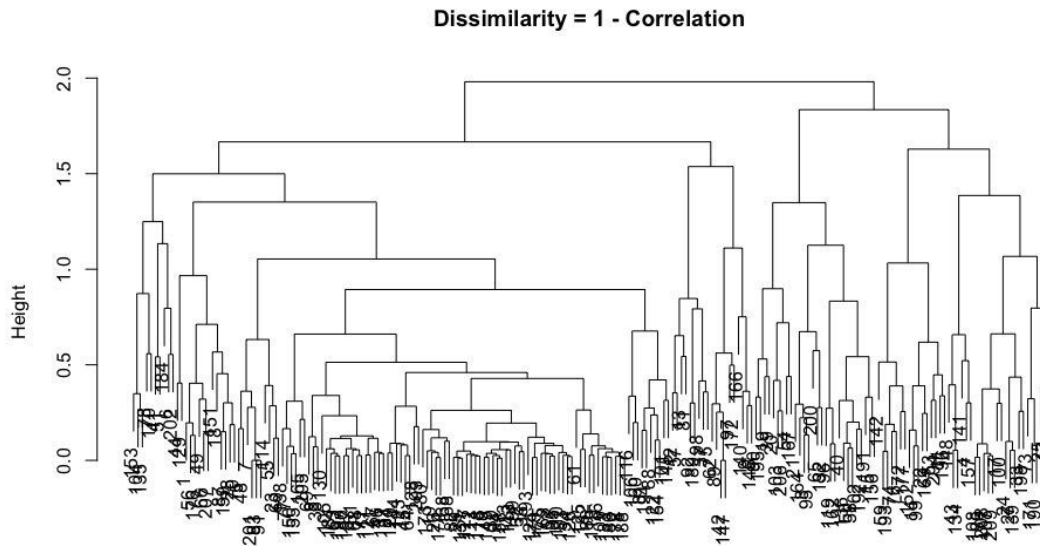
Figure 6. Dendrogram of taxi trips clusters (number represents TLC IDs)

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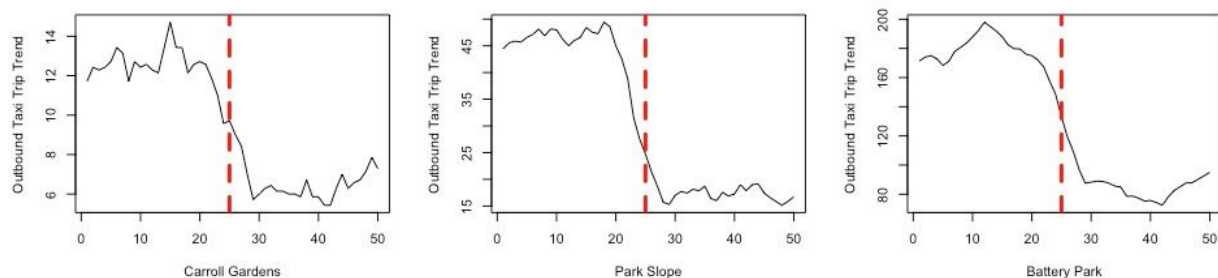
Figure 7. The Trend Components of Taxi Pick-up Time Series in April 2016 and April 2017 of Carroll Garden, Park Slope and Battery Park

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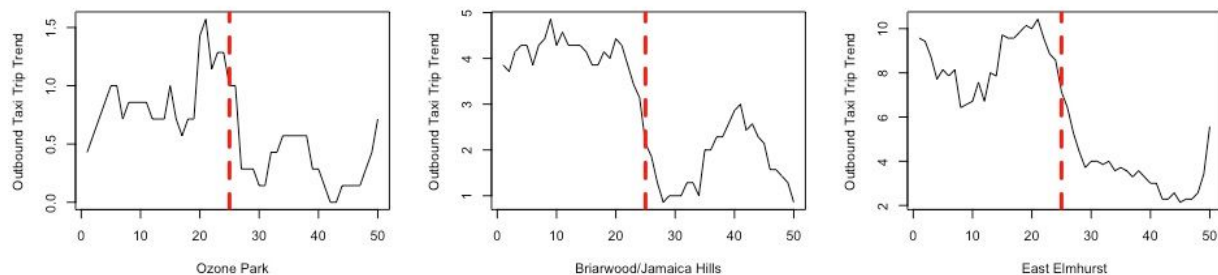
Figure 8. The Trend Components of Taxi Pick-up Time Series in April 2016 and April 2017 of Ozone Park, Briarwood/Jamaica and East Elmhurst

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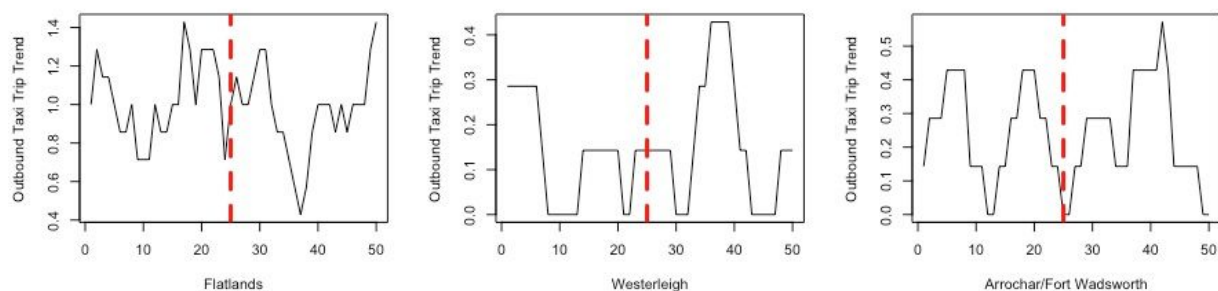
Figure 9. The Trend Components of Taxi Pick-up Time Series in April 2016 and April 2017 of Flatlands, Westerleigh and Arrochar/Fort Wadsworth

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.
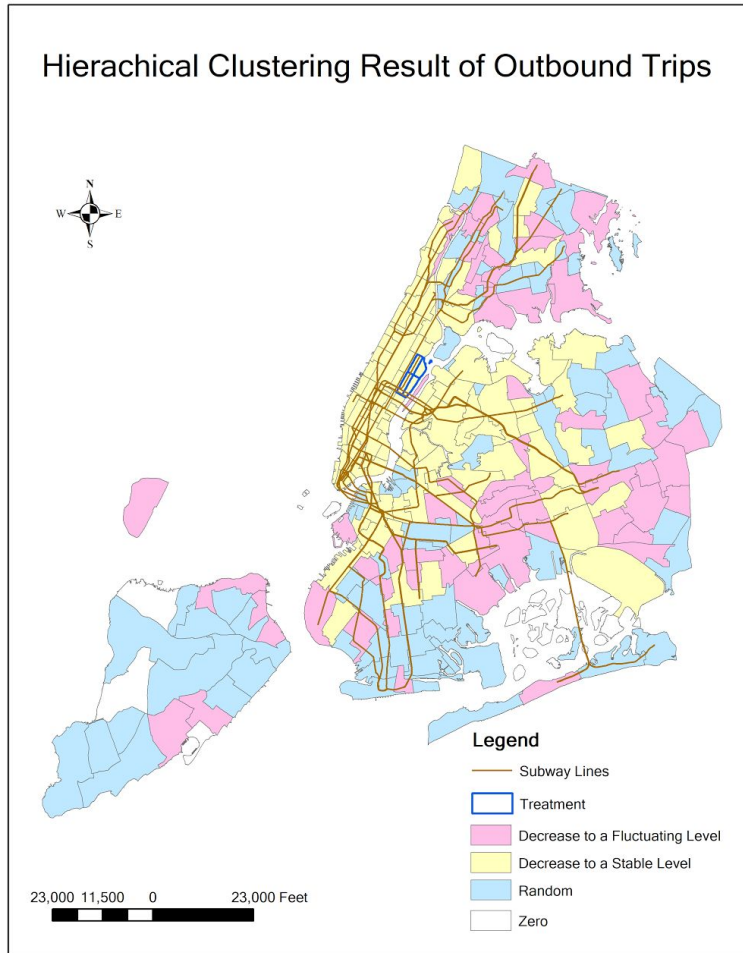
Figure 10 shows the spatial relation for the cluster results. The taxi zones following the decrease-then-stable pattern locate mainly in Manhattan, zones in the Bronx, Queens and Brooklyn near Manhattan and zones near airports. The decrease-then-stable zones are highly overlapped with the districts passed 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

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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**