# Outline

- Changes to the topic
  - Shift from trying to predict changes in dynamics to instead focusing on how much of an impact each travel mode makes
- Changes to the timeline
  - Need to create a timeline
  - retroactively mark when progress has been made. Look forward to what progress still needs to be done.
- Review of the original timeline:
  - more detailed information on what has changed for the project
- A more detailed version of the methods to be applied.

# A Prediction on the Effect of the Proposed Triboro Line: Project Update

Timothy Miller
Dept. of Geography and Environmental Science, Hunter College
GTECH 70500: Spatial Data Analysis Professor Jochen Albrecht November 1, 2022

## Outline

This report documents the progress made on during research into possible effects of the proposed Triboro line on the transportation dynamics of Manhattan, The Bronx, Brooklyn, and Queens. The report will: - review the original research proposal - share results of the exploratory spatial data analysis - explore the availability of required data - reexamine the research question - update the research goals and strategies

## Original Research Proposal

The original research question examined the number of total trips that would be generated by the Triboro line. It also attempted to quantify the total number of trips that would be converted from cars to the subway. This proposal was submitted on Sept 13. After being advised that I would need to provide a list of data needs and a conceptual, I resubmitted an updated project proposal on Sep 27 that included the conceptual model shown in Figure 1 and the list of data needs shown in Table 1. After outlining a general research approach, I finding and examining relevant data.

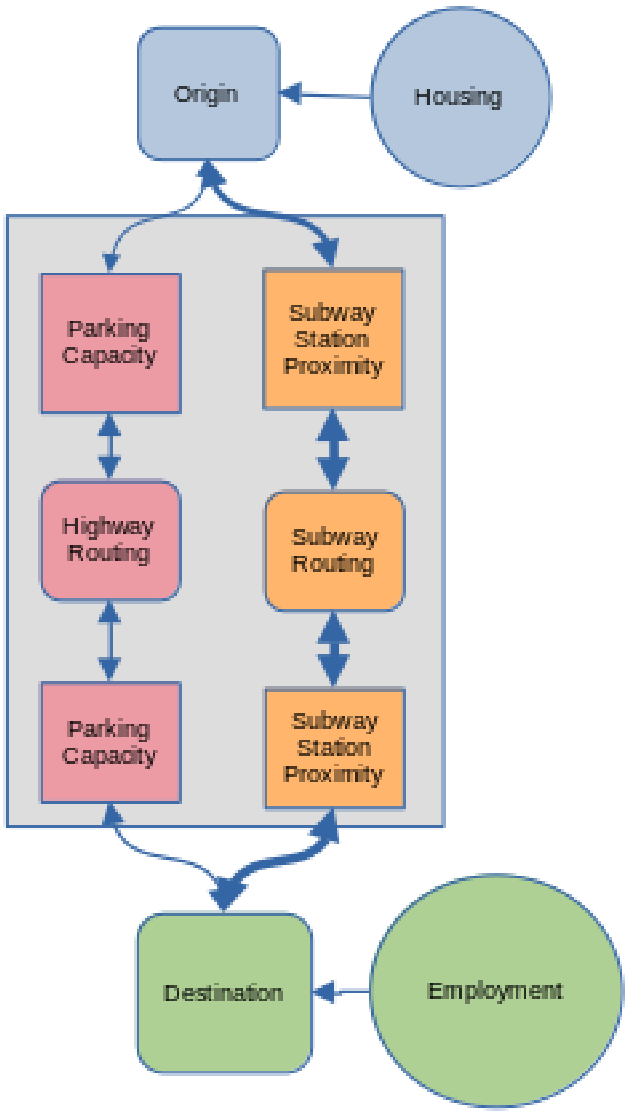



Figure 1: original conceptual model of transportation dynamics

**Data Needs Inventory**

| Metric | Data | Potential Source |
|---|---|---|
| Abundance of Housing | Household population | US Census |
| Abundance of Employment | Employment prevalence | US Census,<br>Bureau of Labor Statistics |
| Highway routes | Highway infrastructure | OpenStreetMap,<br>Google Maps |
| Highway utilization | Highway traffic counts | NYC DOT |
| | Highway travel times | NYC DOT<br>Google Maps & APIs |
| Parking availability | Parking infrastructure | NYC DOT and Planning |
| Parking utilization | Parking counts | NYC DOT |
| Subway routes | Subway infrastructure | NYC Open Data |
| | Subway travel times between stations | NYC Open Data |
| Subway stations | Subway infrastructure | NYC Open Data |
| Subway utilization | AM station entrance counts (Commute origin) | NYC Open Data |
| Assume AM and PM commutes are reciprocals to capture commute start and end | PM station entrance counts (Commute destination) | NYC Open Data |
| Actual Desire Lines | Origin and destination | LODES |

Table 2: original identified data needs inventory

## Exploratory Spatial Data Analysis

After being provided the Longitudinal Employer-Household Dynamics (LEHD) Origin-Destination Employment Statistics (LODES) data and receiving the spatial flows lecture, I began exploring the commute data for the boroughs of interest. The exploratory process helped direct the research question, narrow the study area, and focus the statistical tests.

Required libraries imported directly below

```r
# Data cleaning and organizing
library(tidyverse)
# Import geojson in an sf compatible format
library(geojsonsf)
# Manage spatial data
library(sf)
# Map the geospatial results
library(tmap)
# Prevent use of scientific notation for coordinates
options(scipen = 999)
```

Required data imported throughout the exploration process - Origin and Destination data for NYS in 2019 at the block level - NYC census tract borders - Borders of NYC boroughs - Equivalency of neighborhood tabulation areas to census tracts

**Select the resolution of the study area.**

LODES data are provided at the block level. However, the research question relates to trips that require the highway or subway system. Census blocks for NYC are generally small enough that people can walk between them. Because the research question is not interested in these trips, we can consolidate these trips into census tracts.

Figure 2 indicates that it is also feasible to walk between them. We can generally estimate the distance from the center of each tract to its edge. This will help quantify inter-tract walk-ability. Let us consider a distance below 3000 meters to be walk-able. Though census tracts are irregularly shaped, let us model them as circles to achieve a generally estimate. With this model, we find the average census radius is around 1000 meters. This is well below our walk-ability threshold.

NYC provides a higher level of aggregation than the census tract. The Neighborhood Tabulation Area (NTA) groups census tracts in a way that generally maps to neighborhoods throughout this city. They are mapped in Figure 3 and have an estimated average radius of 3500 meters. NTAs generally represent the minimum distance for trips that would benefit from the subway or highway system. They will be used for the remaining analyses.

```r
# Map borough of interest census tracts
bois_names <- c("Manhattan", "Bronx", "Brooklyn", "Queens")
bois_census_tract_borders <- geojson_sf('./data/nyc_2010_census_tract_borders.geojson') %>%
  dplyr::filter(BoroName %in% bois_names)

tmap::tm_shape(bois_census_tract_borders) +
  tmap::tm_polygons(
    col = "BoroName",
    title = "Borough"
  )
```

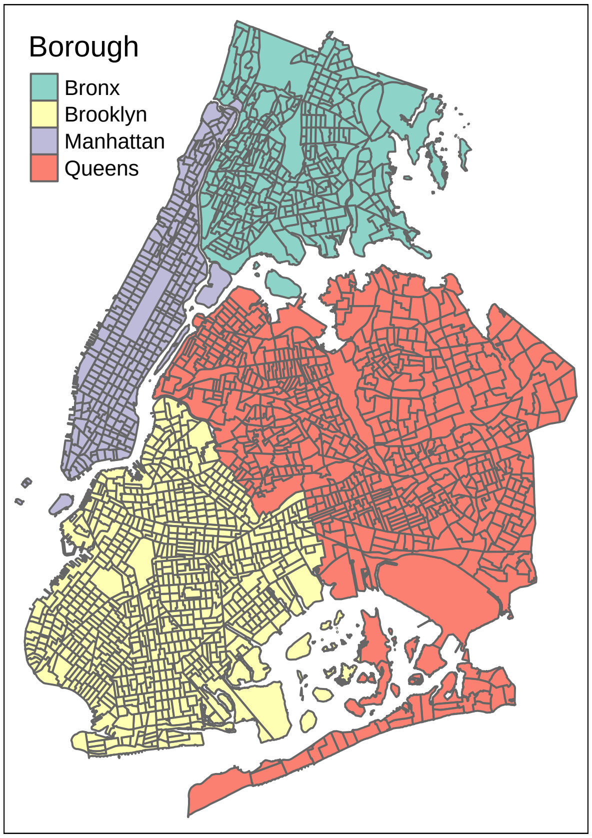



Figure 2: Map of census tracts for the boroughs of interest.

```
# Estimate the average distance from the center to the edge of tract
avg_tract_area <- sum(bois_census_tract_borders$Shape__Area)/ length(bois_census_tract_borders$Shape__Ar
avg_tract_radius <- sqrt(avg_tract_area/pi)
sprintf("Estimate of average distance from the center to the edge of a tract: %s m", avg_tract_radius)
```

```
## [1] "Estimate of average distance from the center to the edge of a tract: 1026.25027690303 m"
```

```
# Map borough of interest ntas
bois_nta_borders <- geojson_sf('./data/nyc_2010_nta_borders.geojson') %>%
  dplyr::filter(BoroName %in% bois_names)

tmap::tm_shape(bois_nta_borders) +
  tmap::tm_polygons(
    col = "BoroName",
    title = "Borough"
  )
```

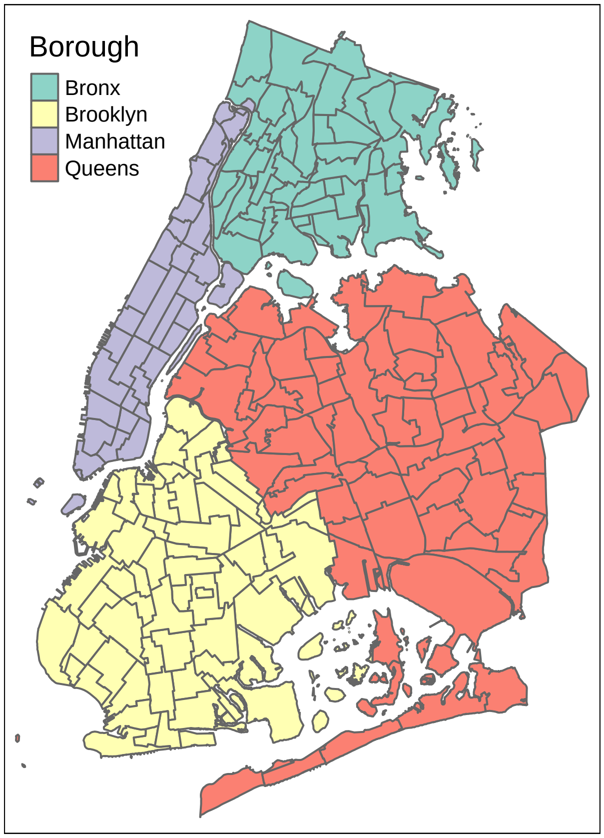



Figure 3: Map of NTAs for boroughs of interest

```
# Estimate of average distance from center to edge of nta
avg_nta_area <- sum(bois_nta_borders$Shape__Area) / length(bois_nta_borders$Shape__Area)
avg_nta_radius <- sqrt(avg_nta_area/pi)
sprintf('Estimate of average distance from center to edge of nta: % s m', avg_nta_radius)
```

```
## [1] "Estimate of average distance from center to edge of nta: 3506.89826880527 m"
```

### Demonstrate the disparity between Manhattan and the other boroughs of interest

After selecting NTAs as the boundaries, I began to explore the trip data for each neighborhood. Before the exploratory process, I expected Midtown Manhattan to have the greatest number of trips. However, I did not anticipate the disparity between Midtown Manhattan and the rest of the boroughs of interest. Figure 4 shows that Midtown Manhattan has tens and even hundreds of thousands more trips than other neighborhoods. Figure 5 shows an overwhelming proportion of trips end in Midtown Manhattan. This disparity would like drown out the transportation effects for other neighborhoods.

*Pre-process the data to count the number of trips between neighborhoods of interest. The trips must start and end in the city. They must also start and end in different neighborhoods. Finally, we remove park ntas; they do not represent a single geographic area and they are not expected to have significant work commute activity.*

```
# Create table to relate NTAs to their component census tracts
bois_county_tract_nta_equiv <- readxl::read_xlsx('./data/nyc_2010_census_tract_nta_equiv.xlsx') %>%
  filter(borough_name %in% bois_names) %>%
  mutate(county_tract = str_c(`county_code`, `census_tract`)) %>%
  select("county_tract", "nta_code")

# Reduce NYS origin destination data to only ntas of interest
```

```r
bois_county_codes = c("061", "005", "047", "081") # Manhattan, Bronx, Brooklyn, Queens
bois_park_ntas <- c("BX10", "BX99", "BK99", "MN99", "QN99")
bois_nta_ods <- read_csv('./data/ny_od_main_JT00_2019.csv') %>%
  # Select only tracts within the boroughs of interest
  dplyr::filter(
    stringr::str_sub(as.character(w_geocode), 3, 5) %in% bois_county_codes &
      stringr::str_sub(as.character(h_geocode), 3, 5) %in% bois_county_codes
    ) %>%
  # Create fields specifically for home counties and tracts
  dplyr::mutate(w_county_tract = stringr::str_sub(as.character(w_geocode), 3, 11)) %>%
  dplyr::mutate(h_county_tract = stringr::str_sub(as.character(h_geocode), 3, 11)) %>%
  # Narrow table down to tracts and all jobs
  dplyr::select(h_county_tract, w_county_tract, S000) %>%
  # Relate tracts with ntas
  dplyr::left_join(bois_county_tract_nta_equiv, c("h_county_tract" = "county_tract")) %>%
  dplyr::rename(h_nta_code = nta_code) %>%
  dplyr::left_join(bois_county_tract_nta_equiv, c("w_county_tract" = "county_tract")) %>%
  dplyr::rename(w_nta_code = nta_code) %>%
  # Remove trips within the same nta, only inter-nta trips are of interest
  dplyr::filter(w_nta_code != h_nta_code) %>%
  # Remove trips involving park NTAs, they are not true neighborhoods
  dplyr::filter(!(w_nta_code %in% bois_park_ntas) & !(h_nta_code %in% bois_park_ntas)) %>%
  # Label trips based on home and work ntas
  dplyr::mutate(od = str_c(h_nta_code, w_nta_code)) %>%
  # Count the number of trips made between these ntas and in this direction
  dplyr::group_by(od) %>%
  dplyr::summarise(
    h_nta_code,
    w_nta_code,
    S000 = sum(S000),
    ) %>%
  # Remove duplicate entries
  unique()
```

Map the distribution of work trips that end in each neighborhoods of interest.

```r
## utility function
get_nta_dest <- function(ods_of_interest) {
  ods_of_interest %>%
    dplyr::group_by(w_nta_code) %>%
    dplyr::summarise(
      w_nta_code,
      S000 = sum(S000)
    ) %>%
    unique() %>%
    left_join(bois_nta_borders, c("w_nta_code" = "NTACode")) %>%
    st_as_sf()
}

# reduce origin destination data to counts of trips ending in an nta
# associated these trips with the work nta geography
bois_nta_dest <- bois_nta_ods %>%
  dplyr::group_by(w_nta_code) %>%
  dplyr::summarise(
```

```
    w_nta_code,
    S000 = sum(S000)
  ) %>%
  unique() %>%
  left_join(bois_nta_borders, c("w_nta_code" = "NTACode")) %>%
  st_as_sf()

tmap::tm_shape(bois_nta_dest) +
  tmap::tm_polygons(
    col = "S000",
    style = "jenks",
    title = "Trips to work in NTA",
    legend.outside.width = 0.6
  ) +
  tmap::tm_layout(
    legend.outside = TRUE,
  )
```

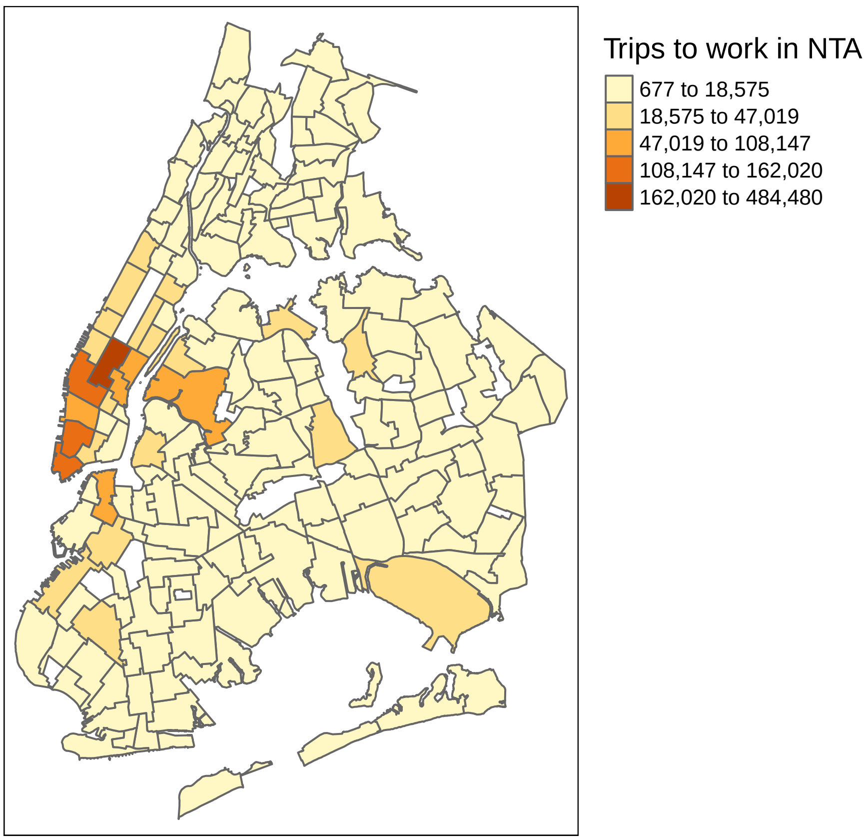



Figure 4: Distribution of work trips that end in each neighborhood. Each trip must start in the boroughs of interest. It must also end in a different neighborhood than it started.

Define the desire lines for work trips throughout the boroughs of interest

```
# Points on surface
bois_nta_pos <- bois_nta_borders %>%
  dplyr::mutate(geometry = sf::st_point_on_surface(geometry))
```

```
## Warning in st_point_on_surface.sfc(geometry): st_point_on_surface may not give
```

```
## correct results for longitude/latitude data
```

```r
## utility function
get_nta_od_lines <- function(nta_ods_of_interest) {
 nta_ods_of_interest %>%
    dplyr::left_join(bois_nta_pos, c("h_nta_code" = "NTACode")) %>%
    dplyr::rename(h_geometry = geometry) %>%
    dplyr::left_join(bois_nta_pos, c("w_nta_code" = "NTACode")) %>%
    dplyr::rename(w_geometry = geometry) %>%
    dplyr::mutate(geometry = sf::st_union(h_geometry, w_geometry))%>%
    dplyr::mutate(geometry = sf::st_cast(geometry, "LINESTRING")) %>%
    dplyr::select("od", "S000", "geometry") %>%
    sf::st_as_sf()
}

bois_nta_od_lines <- get_nta_od_lines(bois_nta_ods)

tmap::tm_shape(bois_nta_borders) +
  tmap::tm_polygons(
    col = "BoroName",
    title = "Borough",
  ) + tmap::tm_shape(dplyr::filter(bois_nta_od_lines, S000 > 5000)) +
  tmap::tm_lines(
    col = "#212121",
    lwd = "S000",
    title.lwd = "Trips",
  ) + tmap::tm_layout(
    legend.outside = TRUE
  )
```

```
## Legend labels were too wide. Therefore, legend.text.size has been set to 0.6. Increase legend.width
```

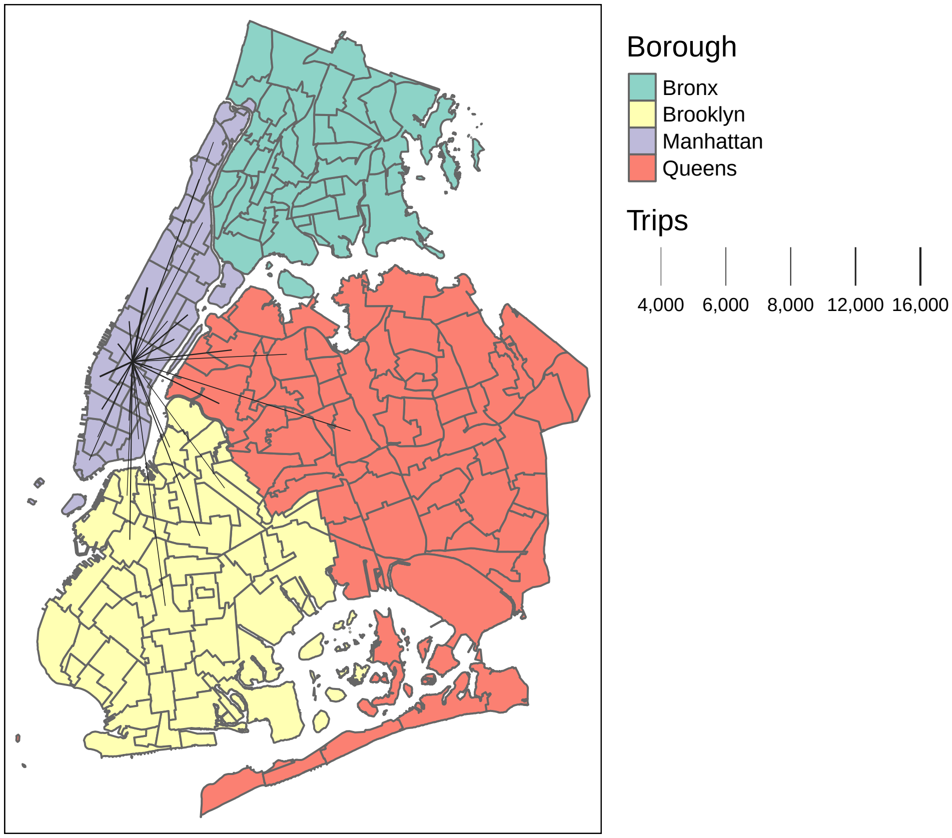



Figure 5: Desire lines for inter-NTA trips

### Examine trips made within the same borough

Define the most origin destination profiles for trips within the same borough

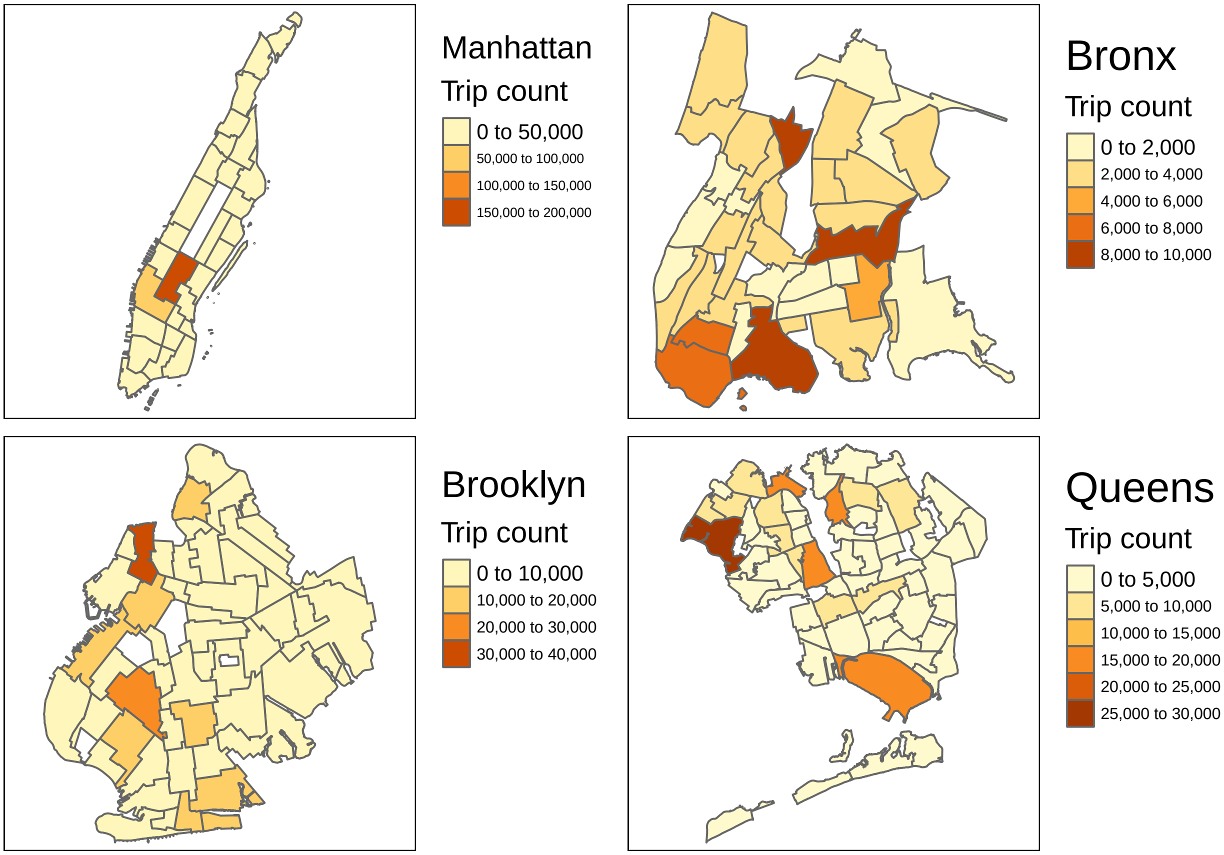
```
## NTA borders for each borough
mn_nta_borders <- bois_nta_borders %>%
  dplyr::filter(BoroName == "Manhattan")
bx_nta_borders <- bois_nta_borders %>%
  dplyr::filter(BoroName == "Bronx")
bk_nta_borders <- bois_nta_borders %>%
  dplyr::filter(BoroName == "Brooklyn")
qn_nta_borders <- bois_nta_borders %>%
  dplyr::filter(BoroName == "Queens")

## Intra Borough trips
intra_bois_nta_ods <- function(boro_abrv) {
  bois_nta_ods %>%
    dplyr::filter(
      stringr::str_sub(h_nta_code, 1,2) == boro_abrv &
      stringr::str_sub(w_nta_code, 1, 2) == boro_abrv
    )
}
mn_nta_ods <- intra_bois_nta_ods("MN")
bx_nta_ods <- intra_bois_nta_ods("BX")
bk_nta_ods <- intra_bois_nta_ods("BK")
```

```r
qn_nta_ods <- intra_bois_nta_ods("QN")


## Most popular destinations for trips within a Borough
mn_nta_dest <- get_nta_dest(mn_nta_ods)
bx_nta_dest <- get_nta_dest(bx_nta_ods)
bk_nta_dest <- get_nta_dest(bk_nta_ods)
qn_nta_dest <- get_nta_dest(qn_nta_ods)

mn_dest_map <- tmap::tm_shape(mn_nta_dest) +
  tmap::tm_polygons(
    col = "S000",
    title = "Trip count"
  ) + tmap::tm_layout(
    legend.outside = TRUE,
    title = "Manhattan"
  )
bx_dest_map <- tmap::tm_shape(bx_nta_dest) +
  tmap::tm_polygons(
    col = "S000",
    title = "Trip count"
  ) + tmap::tm_layout(
    legend.outside = TRUE,
    title = "Bronx"
  )
bk_dest_map <- tmap::tm_shape(bk_nta_dest) +
  tmap::tm_polygons(
    col = "S000",
    title = "Trip count"
  ) + tmap::tm_layout(
    legend.outside = TRUE,
    title = "Brooklyn"
  )
qn_dest_map <- tmap::tm_shape(qn_nta_dest) +
  tmap::tm_polygons(
    col = "S000",
    title = "Trip count"
  ) + tmap::tm_layout(
    legend.outside = TRUE,
    title = "Queens"
  )
tmap::tmap_arrange(mn_dest_map, bx_dest_map, bk_dest_map, qn_dest_map, nrow = 2, ncol = 2)
```




Total trips in each borough

```
print("Intra borough trips")
```

```
## [1] "Intra borough trips"
```

```
sprintf("Manhattan: % s", sum(mn_nta_ods$S000))
```

```
## [1] "Manhattan: 508873"
```

```
sprintf("Bronx: % s", sum(bx_nta_ods$S000))
```

```
## [1] "Bronx: 114719"
```

```
sprintf("Brooklyn: % s", sum(bk_nta_ods$S000))
```

```
## [1] "Brooklyn: 370256"
```

```
sprintf("Queens: % s", sum(qn_nta_ods$S000))
```

```
## [1] "Queens: 265386"
```

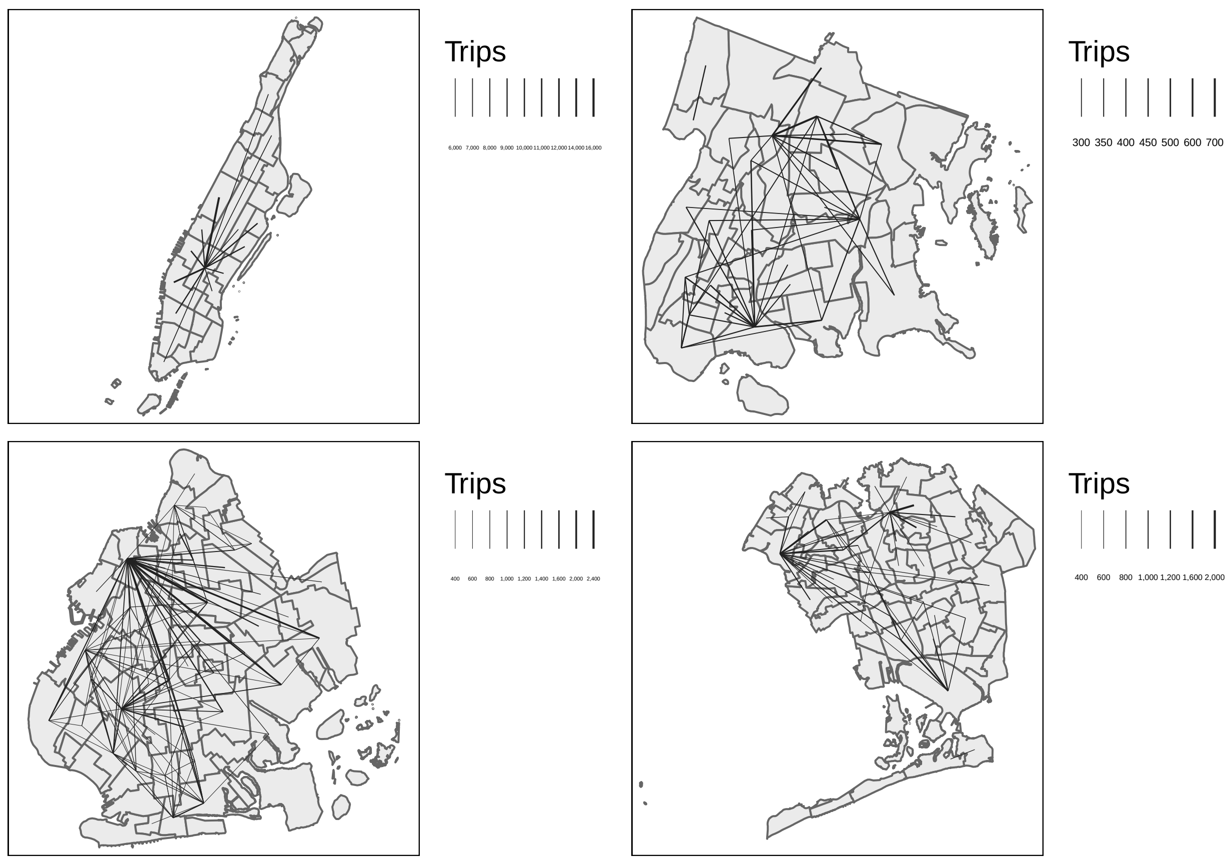
Desire lines for intra borough trips

```
mn_nta_od_lines <- get_nta_od_lines(mn_nta_ods)
bx_nta_od_lines <- get_nta_od_lines(bx_nta_ods)
bk_nta_od_lines <- get_nta_od_lines(bk_nta_ods)
qn_nta_od_lines <- get_nta_od_lines(qn_nta_ods)

create_od_lines_map <- function(borders, lines, borough) {
  return(
```

```
    tmap::tm_shape(borders) +
 tmap::tm_polygons(
    col = "#ebebeb",
    title = borough
  ) + tmap::tm_shape(lines) +
  tmap::tm_lines(
    col = "#212121",
    lwd = "S000",
    title.lwd = "Trips"
  ) +
  tmap::tm_layout(
    legend.outside = TRUE
  )
  )
}

mn_nta_od_lines_map <- create_od_lines_map(mn_nta_borders,
                                           dplyr::filter(mn_nta_od_lines, S000 > 6000),
                                           "Manhattan"
                                           )
bx_nta_od_lines_map <- create_od_lines_map(bx_nta_borders,
                                           dplyr::filter(bx_nta_od_lines, S000 > 300),
                                           "Bronx"
                                           )
bk_nta_od_lines_map <- create_od_lines_map(bk_nta_borders,
                                           dplyr::filter(bk_nta_od_lines, S000 > 500),
                                           "Brooklyn"
                                           )
qn_nta_od_lines_map <- create_od_lines_map(qn_nta_borders,
                                           dplyr::filter(qn_nta_od_lines, S000 > 500),
                                           "Queens"
                                           )
tmap::tmap_arrange(
  mn_nta_od_lines_map,
  bx_nta_od_lines_map,
  bk_nta_od_lines_map,
  qn_nta_od_lines_map,
  nrow = 2,
  ncol = 2)
```




**Updated approach**

- Network auto-correlation of OD desire lines for 2019
- Network auto-correlation of MTA system
- Network auto-correlation of Highway system
- Network correlation of contiguous NTAs
- Regression to compare the MTA and Highway systems, to see which has the greatest effect
- Is there are way to measure the shift in the networks?

Started with interest in Triboro line ridership - Interest in the four boroughs that are severed by the subway system - Manhattan overwhelms the travel patterns throughout the boroughs of interest - Insufficient data to track the total ridership and the means - Travel surveys did not offer the level of detail or confidence - Shifted to looking specifically at work commuting patterns within a single borough - Focused on what correlation each transporation system has with the OD patterns