# Spatial temporal analysis of COVID-19's impact on human mobility in NYC

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**Abstract**

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## 1 Introduction

Since the World Health Organization declared the novel coronavirus (COVID-19) outbreak a global pandemic on 11th March in 2020, the disease has influenced every part of people's daily life and caused more than six million deaths globally (Johns Hopkins Coronavirus Resource Center, 2022). Mobility pattern tracks human movement behavior, which is critical to understand, evaluate and predict the pandemic transmission. Commuting and large-scale gathering aggravate pandemic transmission, while the onset of COVID-19 prevents social activity and lower travel behavior. Thus, many non-pharmacological policies such as quarantines, travel restriction, social distancing has been implemented by governments to prevent the spread of COVID-19.

As the most populous city in the United States with 8.8 million people distributed over 300.46 square miles (U.S Census Bureau, 2020), New York City has experienced widespread transmission and high infection rate since the first confirmed case on March 1st 2020. At the end of March 2020, NYC arrived a peak of COVID-19 and became the pandemic epicenter (Cordes I& Castro, 2020) with a weekly mean of 5132 diagnosed cases and 1,566 hospital admissions. Identifying the spatio-temporal changes of human mobility pattern before, during and after the peak of COVID-19 is important to analyze COVID-19's impact on individuals. In addition, analyzing mobility changes under the contextual backgrounds suggests the heterogeneity of COVID-19's impacts in different groups. For example, high-income individual may choose to decrease their visits to wholesale markets and restaurants and use takeaways services to buy necessary foods. However, people with low- or moderate- incomes may have no choice but to leave home to buy food with higher risk of infection.

Therefore, this objective of this study is to study the spatio-temporal changes of mobility pattern in NYC in March 2019, March 2020 and March 2021 and analyze the social equity issues caused by the pandemic. The research is aimed to answer following question:

1. What is the spatial distribution of visit counts for different categories?
2. What is the temporal change of mobility pattern before, during and after COVID-19?
3. How do the COVID-19 influence individual's travel behaviors in different contexts?

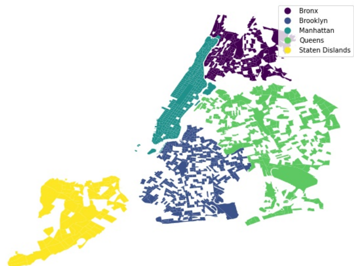



Figure 1: Study Area

## 2 Literature Review

To be finished

## 3 Data

The mobility information was provided by the pattern dataset and core places dataset from Safegraph. Safegraph is a data company that aggregates anonymized location data from third-party applications. Core place dataset are defined as any location humans can visit with the exception of single-family homes with 84717 point of interests (POI) in total, which encompasses a diverse set of places ranging from restaurants, grocery stores, and malls; to parks, hospitals, museums, offices, and industrial parks. Pattern dataset records the block-group-level mobility information such as visitor and visit counts to POI. However, this dataset does not cover all actual visitors but rather a subset of users that have smartphones and enabled their GPS information in various apps (Sevtsuk, 2021).

Socio-economic information such as race and income was from the American Community Survey (ACS) 2015-2019 5-year data.

In addition, the geographic base map was from the US Census Bureau's TIGER 2020 Census Tracts (clipped to shoreline) data products.

| Data | Geographic Level | Source |
|---|---|---|
| Mobility Pattern in March 2019 | Block Group | Safegraph |
| Mobility Pattern in March 2020 | Block Group | Safegraph |
| Mobility Pattern in March 2021 | Block Group | Safegraph |
| Core Place | Block Group | Block Group |
| Demographic Data (e.g. income, race) | Census Tract | ACS 2019 5-year data |
| Geographic boundary | Census Tract | US Census Bureau |

Table 1: Data source

# 4 Methods

Firstly, the monthly mobility pattern data in March in 2019, 2020 and 2021 were collected from Sagegraph and merged with core place dataset to get information about the POI's naics code. The merged data were aggravated to the tract level and map as polygon with geometry data from the U.S. Bureau. Secondly, this study analyzed the spatial distribution of people's visits to public places in NYC with Moran's I. Moran's I is a correlation coefficient to measures the similarity in neighboring places defined as Equation (1) [Mor50]. Large positive Moran's I (close to 1) indicates that strong positive auto0correlation, area with similar values cluster together. Large negative values (close to -1) indicate strong negative auto-correlation, areas with dissimilar values cluster together.

$$\frac{n}{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} \left(X_i - \bar{X}\right) \left(X_j - \bar{X}\right)}{\sum_{i=1}^{n} \left(X_i - \bar{X}\right)^2} \tag{1}$$

In Equation (1), $n$ is the number of observations. $X_i$ is the variable value at particular location i, which is the visit count at census tract $i$. $X_j$ is the variable value at another location $j$. $\bar{X}$ is the mean of the variable X.$w_{ij}$ is the spatial weights between place $i$ and place $j$. When places i and j are neighbors, $w_{ij}$ is close to 1, while they are not neighbors, $w_{ij}$ equals zero. Neighbors are defined by queen criterion, which are places places that share a common boundary or vertex. Global Moran's I was calculated to examine the existence of spatial clustering in visit count. To evaluate the extent of spatial auto-correlation between place i and its vicinity, the local Moran's I was calculated to identify clustering pattern on map. The significance assessment was calculated by pseudo p-value with 999 random permutation. All spatial auto-correlation analysis was calculated by using GeoDa 1.20.
Thirdly, the temporal changes of visit count between two years was calculated as Equation(2):

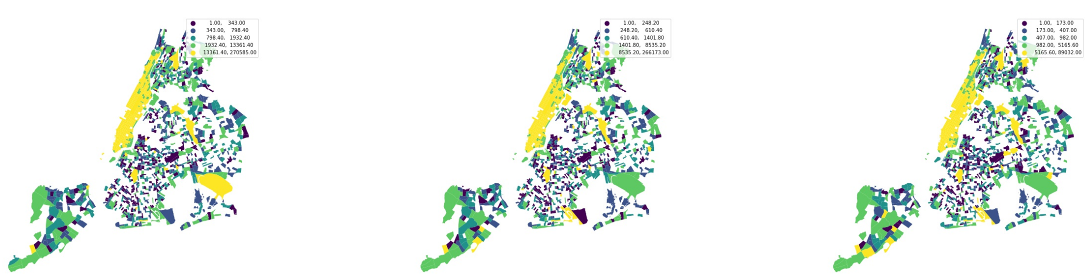
$$\text{change percentage } = \begin{cases} \frac{v_{t_1} - v_{t_0}}{v_{t_0}} \times 100\%, & v_{t_0} \neq 0 \\ \quad 100\%, & v_{t_0} = 0 \end{cases} \tag{2}$$

In Equation (2), $v_{t_0}$ is the variable value at $t_0$ time, and $v_{t_1}$ is the variable value at $t_1$ time, and $t_0 \geq t_1$. If $t_0 = 0$, indicating the is no records at corresponding categories when time was $t_0$.
Lastly, combined with ACS 5-year data, we analyzed the mobility pattern in high-and low- income areas as well in white-majority and non-white majority areas.

# 5 Analysis

## 5.1 Spatial analysis

Choropleth maps for the total visits in NYC shows that Manhattan, John F. Kennedy (JFK) International Airport, LaGuardia Airport are the places people visit most often.

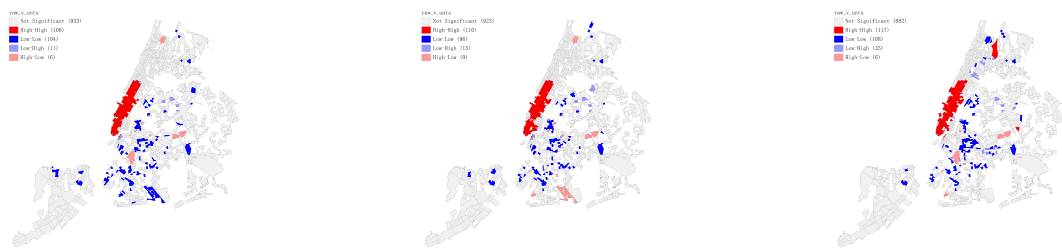


(a) March 2019 (b) March 2020 (c) March 2021

Figure 2: Visit count in different years

### 5.1.1 Spatial auto-correlation analysis

The global Moran's I values of visit count in 2019, 2020 and 2021 are and statistically significantly, indicating the strong clustering pattern in human mobility. The result of local Moran's I is presented in 3. According to the map, the clusters of high visited areas in 2019 were located at Central Park, Midtown and Greenwich Village areas in Manhattan, while the clusters of low visited areas were mainly located at Brooklyn borough and spread in Queens, Staten Island and Bronx boroughs. However, in 2020, the low-visit-clustering area in Brooklyn has decreased. In 2021, northwestern area at the Bronx borough(36005033400) and central Queen borough(tract id:36081022001) became the high-visit-count areas compared to 2019.



(a) March 2019 (b) March 2020 (c) March 2021

Figure 3: Clustering map with local Moran's I statistics

## 5.2 Temporal analysis

Visits to public places has continually decreased from 2019 to 2020 and 2021. Especially, visits to professional and business services, accommodation, food wholesale and retail places decreased more than 50% from 2019 to 2020. This decrease trend extends to 2021 for business categories in transportation and accommodation. Since education, transportation, food, wholesale and retail and health cares are necessary goods and services, following part present detailed analysis of temporal changes of visits to there places before, during and after COVID-19.

### 5.2.1 Education

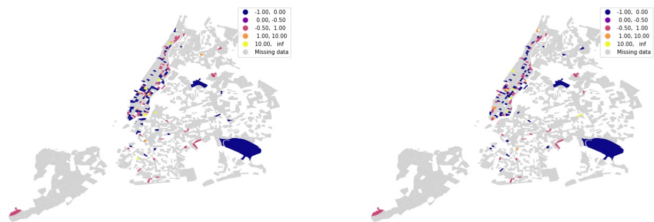
The spatial distribution of change of visits to education POIs indicates that people decreased their visits to education from 2019 to 2020 and 2021 in general. Especially, the clustering pattern of decreasing visit count was observed in Manhattan.

(a) From 2019 to 2020 (b) From 2020 to 2021

Figure 4: Percent change of visit count to Education

### 5.2.2 Transportation

The spatial distribution of change of visits to transportation POI shows that people decreased their visits to education from 2019 to 2020 and 2021 in general. Especially, visits to JFK International Airport and LaGuardia Airport has decreased by 50%.

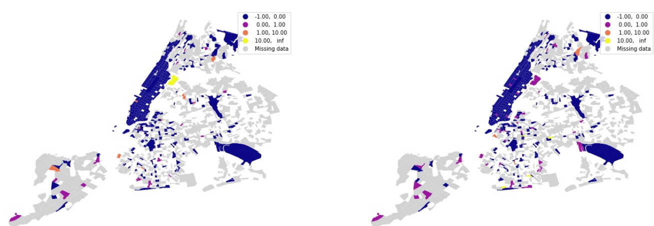



(a) From 2019 to 2020 (b) From 2020 to 2021

Figure 5: Percent change of visit count to Transportation

### 5.2.3 Food

The spatial distribution of change of visits to food POI shows that people decreased their visits to food places from 2019 to 2020 and 2021 in general. Especially, visits to Manhattan and JFK International Airport has decreased by 50%.

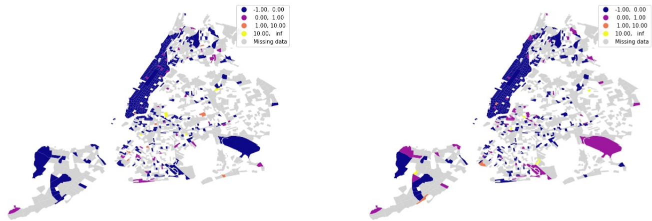



(a) From 2019 to 2020 (b) From 2020 to 2021

Figure 6: Percent change of visit count to Food

### 5.2.4 Wholesale and Retail

The spatial distribution of change of visits to food POI shows that people decreased their visits to food places from 2019 to 2020 and 2021 in general. Especially, visits to Manhattan and JFK International Airport has decreased by 50%.

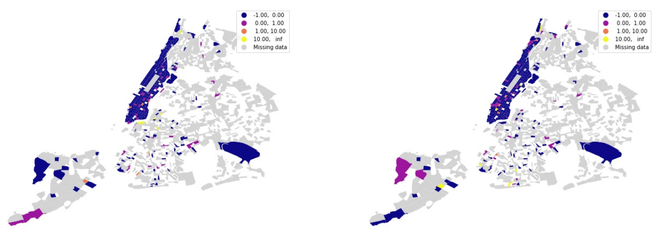



(a) From 2019 to 2020 (b) From 2020 to 2021

Figure 7: Percent change of visit count to Food

#### 5.2.5 Health Care

The spatial distribution of change of visits to food POI shows that people decreased their visits to food places from 2019 to 2020 and 2021 in general. Especially, visits to Manhattan and JFK International Airport has decreased by 50%.




(a) From 2019 to 2020 (b) From 2020 to 2021

Figure 8: Percent change of visit count to Food

# References

[Mor50] Patrick AP Moran. Notes on continuous stochastic phenomena. *Biometrika*, 37(1/2):17–23, 1950.