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Stay-at-Home Order and Spatial Disparities in COVID-19 Pandemic in New York City

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In April 2020, the University at Albany was asked by Gov. Andrew Cuomo to research why communities of color in New York have been disproportionately impacted by COVID-19. The goal of this research, carried out in partnership with the New York State Department of Health and Northwell Health, is to add to the existing well of knowledge about health disparities in New York State by identifying the environmental, socioeconomic and occupational factors that explain why COVID-19 has disproportionately harmed Black and Hispanic New Yorkers and to propose practical intervention strategies to eliminate these disparities and save lives.
For additional information about this project please see: www.albany.edu/mhd or contact Theresa Pardo, Special Assistant to the President and Project Director for this initiative at tpardo@ctg.albany.edu.

White Paper

Stay-at-Home Order and Spatial Disparities in COVID-19 Pandemic in New York City

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Executive Summary

Much of the world has adopted unprecedented lockdown policies as the key method to address the spread of COVID-19; yet, the effect of restricting mobility on pandemic outcomes remain largely unknown. Existing research has focused on infections and deaths at the city/county/state or country level, and significant disparities *within a particular city* has been under-studied. There is a critical and urgent need to assess the effect of restricting mobility on health disparities in this pandemic especially within a city and to identify the appropriate policy intervention for optimal outcomes. In the absence of such knowledge, addressing health disparities and reopening the economy safely before there is a vaccine remain difficult. The overall objective of this research is to determine how mobility restriction policies shape intra-city health disparities in this pandemic. The central hypothesis is that the lockdown policy contributes to spatial disparities in infection and death rates, together with public transit networks, a key mobility enabling infrastructure, and resident socioeconomic indicators.

Using New York City as a case study, this project adopts a spatial method to study infection and death rate at census tract level using multiple sources of data including pandemic, census, transit network, and cellphone mobility data. Findings demonstrate the effectiveness of stay-at-home order. On average, people spent about 20% more time at home in 2020 than in the same period in 2019. With every one percentage point increase in time spent at home in 2020, infections and deaths decrease by 0.5% and 0.7% respectively. Meanwhile, MTA subway train stations and especially bus stops are found to be positively associated with pandemic outcomes, as census tracts with each additional station/stop are expected to have 1.5% more infections and 1.3% more deaths. Socioeconomic factors also shape pandemic outcomes and spatial disparities. Census tracts with a higher concentration of ethnic minorities, higher poverty rates, larger household size, more households living with overcrowding, and larger share of elderly people (60+) have higher infection and death rates. The lack of health insurance is also found to result in higher death rate (not infection rate).

However, Geographically Weighted Regressions (GWRs) demonstrate that the effects of stay-at-home order, public transit system, and socioeconomic indicators vary significantly across space. High-risk census tracts can be identified based on the effect of a specific factor. City-wide clusters (or “New Five Boroughs”) based on similarities in pandemic outcomes and other factors are also identified. While policy interventions such as stay-at-home order are generally applied uniformly across the city, this research shows that its effect is often spatially varied, and localized policy interventions targeting high risk neighborhoods and clusters are needed for more effective results and to minimize impact on vulnerable neighborhoods and subpopulations. Policy implications are recommended.

This research advances our knowledge of health disparities. Through the lens of mobility, this research determines how mobility restriction policy and public transit infrastructure together with socioeconomic indicators shape spatial disparities in pandemic outcomes. This helps us to identify the institutional and environmental sources of health disparities. The adoption of a spatial approach and the focus on the nexus of government policies, the built environment, and mobility potentially can start a new avenue in understanding health disparities.

Overview and Objectives

With a novel coronavirus (COVID-19) and no vaccine yet, the world has adopted mobility restriction as the key measure to control this pandemic; yet, the effect of mobility restriction on pandemic outcomes remain largely unknown. From the draconian sealing-off in Wuhan, China, to nationwide lockdown in Italy, and to statewide stay-at-home orders in the U.S., mobility restriction from various "lockdown policy" has transformed the world beyond recognition. While mobility restriction has been adopted as one of the key responses to pandemic threats in history (e.g. Pyle, 1969; Peiris and Guan, 2004; Bajardi et al., 2011; Wang and Taylor, 2016; Charu et al., 2017), mobility restrictions adopted by governments to contain COVID-19 pandemic are unprecedented with its worldwide scale and long duration. Touted by some as "the Great Equalizer" (Mein, 2020), COVID-19 pandemic has exhibited significant spatial and social disparities in outcomes. Poor neighborhoods and disadvantaged groups such as the elderly and ethnic minorities have suffered disproportionately high rates of infection and death (CDC, 2020; Chen et al., 2020; Thebault et al., 2020; Yancy, 2020). Thus there is a critical need to assess the effect of mobility restriction on health disparities in this pandemic and to identify the appropriate mobility restriction for optimal outcomes. In the absence of such knowledge, it is difficult to adequately address health disparities in this pandemic and safely reopen the economy.

There has been a rapidly growing body of literature devoted to the understanding of the COVID-19 pandemic. Social scientists have reaffirmed human mobility as a main reason for virus transmission in this pandemic (e.g. Goscé et al., 2020; Fang et al., 2020; Coven and Gupta, 2020). However, existing research on COVID-19 and mobility has mainly studied infections and deaths in different cities/counties and countries, while well documented disparities *within the city* have been under-studied. More importantly, while mobility restriction is widely implemented in this pandemic, it remains unclear how the urban mobility environment, defined by both the government's lockdown policy and the public transit system, shape different pandemic outcomes at the neighborhood level.

This research aims to determine how the mobility restriction policy (or stay-at-home order) shapes intra-city health disparities in this pandemic in New York City. The central hypothesis is that while the stay-at-home policy is effective in reducing infections and deaths, its effect varies across space, contributing to spatial disparities in pandemic outcomes. In addition to different resident profiles, uneven mobility infrastructure in the city defined by public transit networks, contribute to spatial disparities. The specific objective is to determine how the stay-at-home order and public transit networks together with sociodemographic factors predict infection and death rate at census tract level.

As the U.S. is entering the second wave of COVID-19 pandemic, the country, and the world, is currently at a critical juncture point of continuing mitigation and maintaining economic vitality. Solid sciences are desperately needed for proper decision-making. This research can provide concrete evidence for local governments to develop appropriate mobility restriction policies not only for COVID-19 pandemic and future epidemics but also for the reopening of the economy. In addition, high-risk neighborhoods can also be identified for localized policy interventions to minimize impact on vulnerable neighborhoods and subpopulations, and to reduce health disparities.

Literature Review

There has been an intensified research interest on COVID-19. While most research is in the medical field, there is also a growing body of research in social sciences devoted to the understanding of the patterns of pandemic outcomes, its driving forces, and its impact on people and the society. The following literature review focuses on disparities in pandemic outcomes, and associated factors including mobility, transport network, and government policies.

Spatial and Social Disparities The COVID-19 pandemic has exhibited significant spatial and social disparities. In addition to regional disparities, poor neighborhoods and disadvantaged groups in the same city seem to suffer disproportionately in terms of infection, hospitalization and deaths despite the same healthcare infrastructure. Research shows that elderly, males, and persons with underlying diseases such as hypertension, diabetes, obesity, cardiovascular diseases and myocardial injury are prone to more severe illness, even fatalities (Shi et al., 2002; Bonow et al., 2020; Grasselli et al., 2020). In the U.S., ethnic minorities, especially African Americans, are more likely to be infected and die. The infection rate among 131 predominantly black counties in the U.S. is more than 3-fold higher, and the death rate is 6-fold higher than that among predominantly white counties (Thebault et al., 2020). Making up only 13% of the total population, African Americans accounted for 23% of deaths from COVID-19 (APC, 2020).

While many suggest unequal socioeconomic status and health conditions may contribute to disparities in pandemic outcomes, it is challenging to actually find sources for the disparity. One main reason is the data limitations, as COVID-19 data is often not reported by race, and if reported by race, the confidentiality rule prevents linking COVID-19 data with other socioeconomic data (Gross et al., 2020). Using individual patient data from Sutter Health, a large healthcare delivery system in northern California, Kristen et al., (2020) find strong evidence for ethnic disparities, as African Americans had 2.7 times the odds of hospitalization *after* adjusting for age, sex, comorbidities and income. Gross et al. (2020) find that mortality rates for Blacks are more than triple the rates for whites *after* correcting for age, and the rates for Hispanics are almost double the rates for non-Hispanic whites. Yancy (2020) concurs that this racial disparity goes beyond concerns of comorbidities, and he suggests where and how African Americans live matter. Many African Americans and other minorities live in poor neighborhoods with high housing density and poor access to healthy foods, factors which not only put them at a higher risk of disease but also make practicing public health safety measures - such as social distancing and mobility restriction – more challenging.

Transport Network and Mobility Many factors contribute to the transmission of infectious diseases. In addition to population density (Meng et al., 2005) and medical infrastructure (Affonso et al., 2004; Meng et al., 2005), transport network and human mobility have long been considered important factors in disease transmission. Studying cholera in the 19th century, Pyle (1969) found that the disease spread through transport networks such as waterway and road systems. More recently, air transport networks and international travel, as well as the subway system in London have been found to be important in disease spread (e.g. Peiris and Guan, 2004; Rvachev and Longini, 1985; Goscé and Johansson, 2018).

For COVID-19 pandemic, scholars have confirmed the importance of transport network and mobility. Wu et al. (2020) argue that through the air and train systems, the virus has already transmitted to other Chinese cities and countries in January 2020 before the lockdown in Wuhan. Using location tracking by mobile phones, Jia et al. (2020) argue that population mobility from Wuhan can predict the subsequent location, intensity and timing of outbreaks in the rest of China, and it outperforms all other measures such as population size, wealth, and distance from the risk source. In the U.S., Harris (2020) argues that the subway system in New York City (NYC) is a major disseminator, if not the principal transmission vehicle, of coronavirus virus at least during the initial spread of this epidemic. Coven and Gupta (2020) argue that disparities in mobility response contribute to much of the observed differences in infection and mortality numbers in NYC. Using mobile tracked locations, they find that residents in richer neighborhoods are substantially more likely to flee the city during the pandemic, while those in low-income, Black, and Hispanic neighborhoods exhibit high intra-city mobility during both work and non-work hours. This difference in mobility demonstrates inequality in shelter-in-place options and contributes to disparities in COVID-19 outcomes. Using data for 3,140 counties, McLaren (2020) find while the share of minority population is strongly correlated with COVID-19 deaths, racial disparity for African Americans and First Nations population does not seem to due to differences in income, poverty rate, education, occupational mix or even access to healthcare insurance. Instead, he finds that a significant portion of the disparity can be sourced to the use of public transit, which also explains the difference between NYC and Los Angeles.

Intervention Policies and Mobility Because of the significance of transport networks and human mobility in the transmission of infectious diseases, restriction on human mobility is one of the key responses to epidemics in history (Bajardi et al., 2011; Wang and Taylor, 2016; Charu et al., 2017). However, a total lockdown policy, with its scale, magnitude and duration as many regions and countries adopted during the COVID-19 pandemic, is unprecedented. Despite its disruptive impact on the economy, scholars find that the lockdown policy has been very effective in lowering infections and controlling the spread of COVID-19. Using machine learning, Qiu et al. (2020) show that the massive lockdown and other control measures in China significantly reduce the virus spread. Their results show that the population outflow from Wuhan poses higher risks to destination cities than other socioeconomic factors such as geographic proximity and similarity in economic conditions. Fang et al. (2020) also find that the strict lockdown policy in Wuhan and consequent reduction in mobility have significantly reduced the total number of infections in China.

However, others criticize the effectiveness of the lockdown policy and mobility restriction in containing COVID-19. For example, Chinazzi et al. (2020) find that travel bans in Wuhan delay the overall epidemic progression by only 3-5 days in China. Their results suggest that early detection, hand washing, self-isolation, and household quarantine are more effective than travel bans in mitigating this pandemic. Lai et al. (2020) also argue that other interventions are more effective than travel bans. They simulate the outbreak across cities in China and consider several non-pharmaceutical interventions deployed in China such as travel bans, contact reductions and social distancing, and early case identification and isolation. They argue that these interventions are all effective in containing the COVID-19 outbreak, but their efficacy varies, with early case detection and contact reduction being the most effective.

The lockdown policy has been implemented unevenly across space with different impacts on COVID-19 outcomes. Comparing China, Italy and the U.S., Ren (2020) argues that the poor coordination between national and local governments, and the piecemeal and delayed policy in the U.S. and Italy have made their lockdown policy less effective in reducing infections and deaths than in China. In the U.S., the lockdown policy has also been implemented differently between regions. Glaeser et al. (2020) study the overall infection rate in five U.S. cities and find mobility reduction has different effects across space and over time. On average, they find about 20% decrease in the number of COVID-19 cases per capita for every 10% decrease in mobility between February and May 2020. However, they find stronger effect in

NYC, Boston, and Philadelphia than in Atlanta and Chicago, and the largest effect is for NYC in the early stages of the pandemic. In Italy, mobility restriction has a stronger impact in municipalities with higher income inequality and lower per capita income as well as those with high fiscal capacities, which demonstrate the social cost of the lockdown policy and the dilemma local governments face (Bonaccorsi et al., 2020). Using mobile phone sighting data, Zhou et al. (2020) simulate the outcomes of different degrees of mobility restriction policy in the city of Shenzhen, China. They find mobility restriction of 20-60% had notable effects in both flattening and delaying the peak, with a larger effect from a higher degree of mobility restriction.

While the literature on COVID-19 is growing rapidly, existing studies have three limitations. First, most studies are conducted at the national and city/county level, with few research at the neighborhood level. Intra-city disparities in pandemic outcomes have been well recognized; yet in-depth analyses beyond mapping infections and deaths have been limited probably due to the lack of data at a smaller spatial scale. Second, most research on mobility uses population movement, such as the number of travelers between cities and countries, and number of trips using cellphone geolocation data, to predict pandemic outcomes. There is little attention to the actual transport networks, while often determines how people move within and between cities, and thus shapes disease transmission. Third, while existing data shows significant spatial inequality in infections and deaths, few studies adopt spatial methods to study this pandemic. Infectious disease is fundamentally a spatial phenomenon with virus transmitted through human contact, and geography is a key part in fight COVID-19 outbreak (Sheppard, 2020). However, the lockdown policy is implemented uniformly within the city, which tends to exacerbate spatial and social inequality as some workers can work from home while others have to commute to work using public transit, thus significantly increases the latter's risk of infection. Given the importance of mobility in epidemics, a location-based prevention and mitigation policy is needed, and a spatial understanding of pandemic outcomes is crucial.

Data and Methods

This research utilizes four types of data, which are merged at the census tract level:

1) **Pandemic data:** COVID-19 infection cases and deaths for zip code zones are released by the NYC Department of Health. The accumulated cases and death toll are between April 6 and August 16, 2020. This data is partitioned into estimates at census tract level based on the area ratio of census tracts within each zip code zone.

2) **Public transit network data**, including the subway and bus systems, accessed through Metropolitan Transportation Authority (MTA) in NYC. Number of bus and subway stations in each census tract is used to indicate the connectivity and mobility infrastructure in each census tract.

3) **Mobility data**. **SafeGraph** provides daily aggregated social distancing metrics based on cellphone data on foot-traffic for each census block group (CBG) (SafeGraph, 2020), which are further aggregated to the census tract level. Important measures include time spent at home, and time spent outside of home. These cellphone data allow us to measure the effectiveness of stay-at-home order and consequent mobility reduction, comparing time spent at home in 2020 to the same period in 2019. Considering the incubation period of symptoms, we

collected the mobility data 14 days prior to our pandemic data period, hence between March 23 and August 2, 2020.

4) **Census data**. 2018 American Community Survey (ACS) 5-year estimates provide sociodemographic factors at the census tract level, such as age structure, average household size, ethnic group composition, education, median household income, poverty level, crowding, and commuting mode.

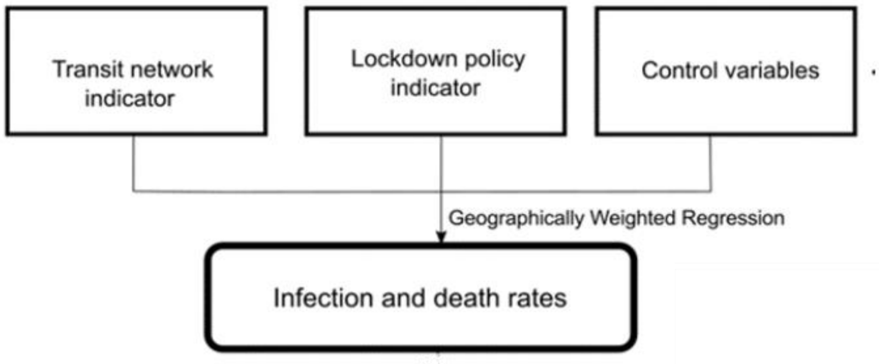

Figure 1. The analytic framework

The analytic framework is illustrated in Figure 1. Non-spatial regressions have been conventionally used to predict health outcomes, which assumes the relationships between explanatory factors and outcomes are the same across space. For infectious diseases which tend to be clustered spatially and diffuse across space, many factors have spatially variant effects. **A spatial approach** is needed to study pandemic outcomes, an intrinsic spatial phenomenon**.** In this study, **Geographically Weighted Regressions (GWRs)** is used to determine how the lock-down policy/stay-at-home order and public transit system, together with other socioeconomic factors, predict infection and death rate at the census tract level. Based on the first law of geography that everything is related but closer things are more related (Tobler, 1970), GWR considers distance between locations as a crucial factor in spatial outcomes and use it as a weight to account for spatial heterogeneity in the association between the outcome and explanatory variables. GWRs can not only determine the spatially varied effects of public transit networks, the lockdown policy/stay-at-home order and other socioeconomic factors in shaping the spatial disparities in COVID-19 outcomes, but also identify census tract clusters with high risks of infections and deaths for targeted policy interventions.

The outcome variables are estimated cumulative infection rate and death rate for each census tract, which are calculated with cumulative cases of infections and deaths during April 6 - August 16, 2020, and the total population of each census tract.

The **key explanatory variables** include the following:

a) *Stay-at-home indicator*: This indicator measures the effectiveness of stay-at-home order and consequent mobility reduction, using SafeGraph cellphone data. It measures the relative change in time spent at home, using the average time spent at home in 2020 and time spent at home during the same period in 2019 per person for each census tract, using the following formular:

$$Stay-at-\ home\ indicator = \frac{Time\ at\ home\ in\ 2020 - Time\ at\ home\ in\ 2019}{Time\ at\ home\ in\ 2019} * 100$$

If the indicator is positive, on average people in the census tract spent more time at home in 2020 than the same time period in 2019, indicating a reduced mobility after stay-at-home order was implemented; if it is negative, on average people spent less time at home in 2020 than in 2019. Zero indicates no change in mobility. The larger the indicator, the more effective the stay-at-home order is and the lower the mobility is. This indicator reflects the effectiveness of the lockdown policy and stay-at-home order in each census tract.

b) *Public transit indicator*: the total number of bus stops and subway stations in the census tract. Census tracts with more MTA stations are more connected with the rest of the city and their residents may have higher mobility and more exposure to COVID-19, which potentially encourage infections and deaths.

c) *Socioeconomic variables* include the following variables at census tract level from ACS:

- Age structure: % of people who are 60+
- Ethnic composition: %Minority, %Black, % Asian, %Hispanic
- Household size: average number of people in each household
- Education: % of people with college+ education
- Occupation 1: % of people in sales, service and office occupations
- Occupation 2: % of people in management, business, science and arts occupations
- Crowding: % of people living in households with more than one person per room
- Poverty: % households in poverty
- Commuting mode: % people using public transit
- Health insurance: % of persons with no health insurance

Regressions are conducted for the period after the stay-at-home order was implemented in late March (effective starting from March 23rd) and until August 16 after all four phases of reopening was implemented.

Findings

1) Infection and death rates vary significantly across census tracts

The average infection rate at the census tract level is 29.3 cases per 10,000 people, and the average death rate is 2.5 per 10,000 people (Table 1). Clearly there is a large variation between census tracts with relatively large standard deviation and maximum value for both infection and death rate.

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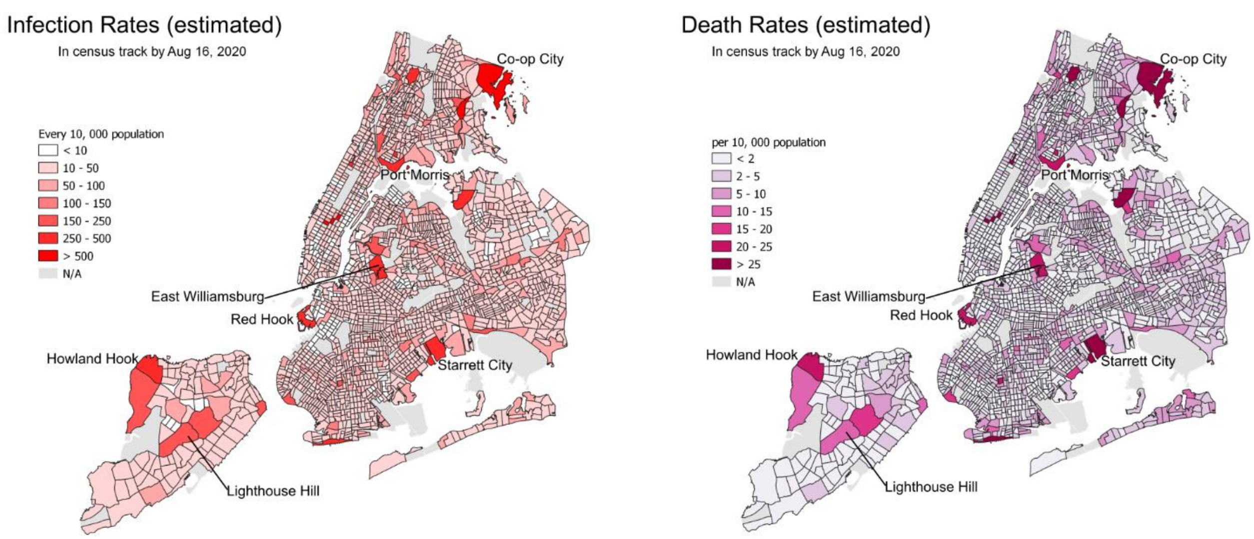
Table 1 Summary Statistics for Infection and Death Rate at Census Tract Level

(Per 10,000 ppl)	Mean	St. Deviation	Median	min	max
Infection rate	29.304	39.360	21.733	0.000	672.241
Death rate	2.515	3.374	1.821	0.000	51.840

Figure 1 shows significant spatial disparity in infection and death rate. While more than 90% of census tracts have relatively low infection (<0.5%, or <50 cases per 10,000 people) and death rate (<0.05% or <5 deaths per 10,000 people), a small number of census tracts have extremely high infection and death rates. There are 15 census tracts with infection rate >2.5% (250 cases/10,000 people) and ten tracts with death rate >0.25% (25 deaths/10,000 people). Clearly there is a high degree of correlation between infection and death rate. Interestingly, each of the five boroughs have some “high risk” census tracts with high infection and death rate, such as Port Ivory Howland Hook in Staten Island, Midtown/Korean Town in Manhattan, East Williamsburg, Red Hook, Coney Island, and Starrett City in Brooklyn, Port Morris, Co-Op City in Bronx, and Flushing in Queens.

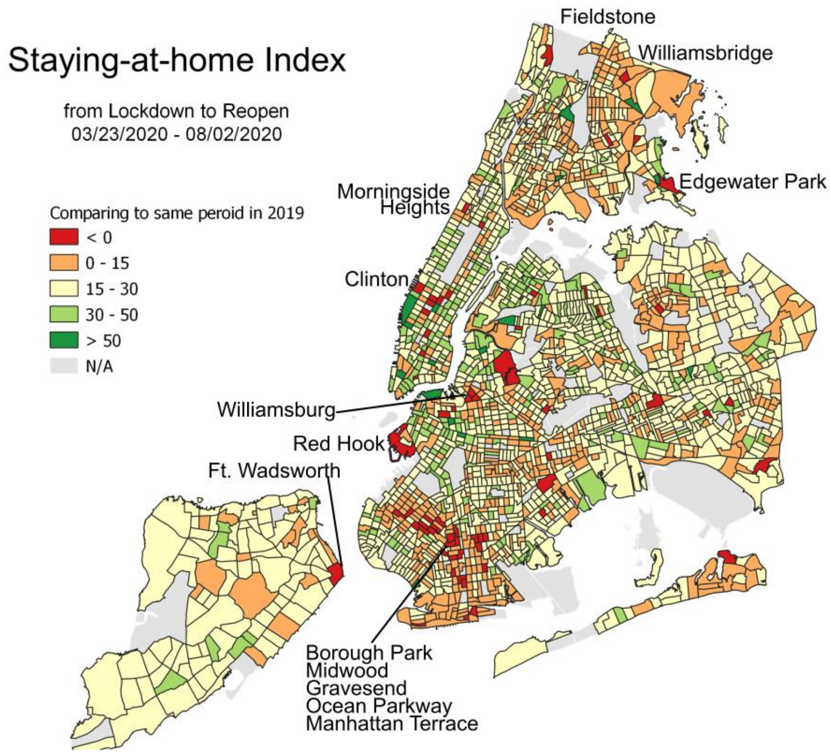
Map 1 Map of Infection and Death Rates



2) The effectiveness of stay-at-home order varies across space

The stay-at-home order is implemented uniformly across the city. However, its effectiveness varies significantly between census tracts. On average, people in each census tract spent about 20% more time at home in 2020 than in the same period in 2019. In more than 25% of census tracts, people on average spent 0-15% more time at home (orange shade on the map); in about 60% of census tracts, people spent 15-30% more time at home (yellow), and in about 13% census tracts, people spent 30% more time at home (greenish shade), which indicates the varied effectiveness of stay-at-home order across space. In other words, people in most part of the city followed the stay-at-home order. Only in about 3% of census tracts (red), people either spend less (0.53%) or the same amount of time (2.62%) at home in 2020, which implies that people did not seem to follow stay-at-home order. These tracts are spread out in all five boroughs, but mostly in Mid-town Manhattan, Forest Hills in Queens, East New York, Borough Park, Midwood in Brooklyn. Some of these census tracts may have many people working in essential business and others such as those in Hasidic Jewish neighborhoods just did not follow the stay-at-home order for religious reasons.

Map 2: Stay-at-home Index and Mobility Reduction in 2020



3) Infection and death rate are significantly associateed with stay-at-home order, public transit system, and resident profiles.

Spearman correlation coefficient indicates the strength and direction of association between two variables. It ranges between -1 and 1, with the value closer to 1 or -1 indicating a stronger positive or negative association. According to Table 2, both infection and death rate have relatively weak but significant associations with stay-at-home index, MTA stops, as well as various socioeconomic indicators for resident profile. First of all, increased time spent at home is associated with lower infection and death rates. This clearly indicates the effectiveness of stay-at-home order on infections and deaths. Secondly, the number of bus and subway stops is positively associated with infection and death rate. The number of MTA stops are likely associated with the demand for public transit and ridership of population in the area. This indicates that the more MTA stops in the census tract, the higher infection and death rate, which demonstrates the importance of public transit in pandemic outcomes and indicates a large number of population riding public transit. Thirdly, the associations with socioeconomic indicators generally conform to conventional knowledge and existing literature. For example, %White, %Asian, %people with college+ education, and %people in professional careers have negative associations with infection and death rate, while %Black, %Hispanic, poverty rate, crowding, household size, %people aged 60+, %people with no health insurance, and %people in sales, services and office occupations all have positive association with infection and death rate. Surprisingly, %people taking public transit has a negative association with infection and death rate. Of course, this indicator is derived from 2018 ACS, thus it is a measure for commuting mode in the pre-pandemic period, not during the pandemic. Census tracts with higher %public transit may be impacted by stay-at-home order more significantly with much reduced mobility, than those with higher shares of private cars, thus have lower infections and deaths.

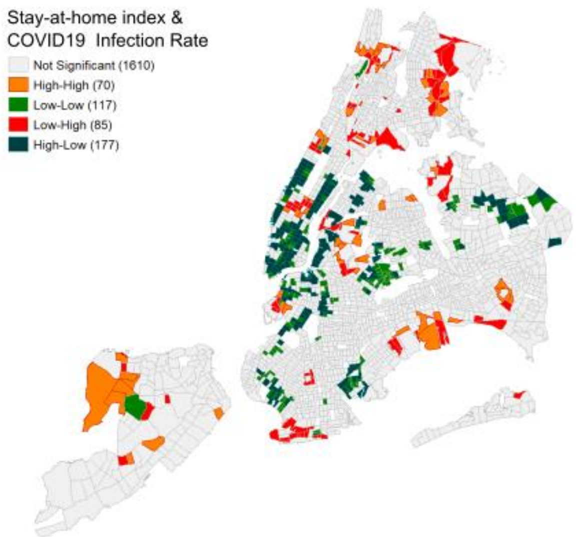
Table 2 Spearman Correlation Coefficients between Infection Rate, Death Rate and Socioeconomic Indicators

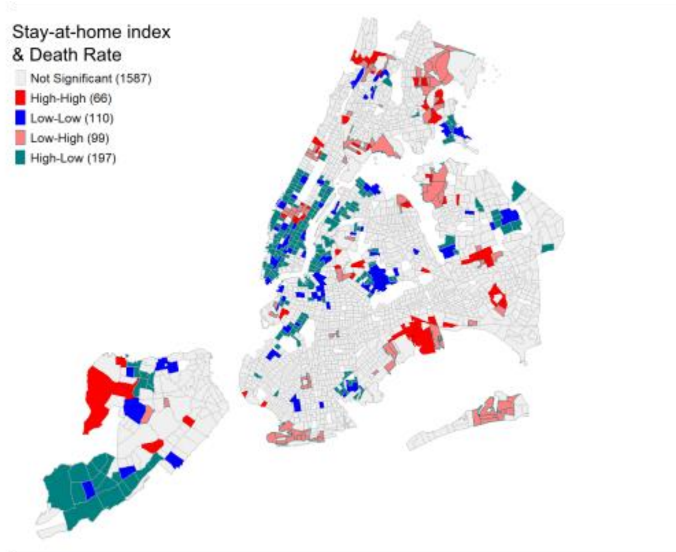
Indicators	Infection rate			Death rate		
	Coefficient	P-Value		Coefficient	P-Value	
Stay-at-home index	-0.153	0.000	***	-0.155	0.000	***
Number of MTA stops	0.109	0.000	***	0.073	0.000	***
White%	-0.223	0.000	***	-0.283	0.000	***
Black%	0.159	0.000	***	0.220	0.000	***
Hispanic%	0.148	0.000	***	0.136	0.000	***
Asian%	-0.125	0.000	***	-0.101	0.000	***
Poverty rate	0.056	0.012	**	0.102	0.000	***
Average # of people in household	0.260	0.000	***	0.189	0.000	***
% people taking public transit	-0.179	0.000	***	-0.064	0.004	***
% household with overcrowding (> one person per room)	0.084	0.000	***	0.026	0.246	
% people with college+ education	-0.229	0.000	***	-0.206	0.000	***
% population aged 60+	0.042	0.056	*	0.083	0.000	***
% people with no health insurance	0.081	0.000	***	0.117	0.000	***
%people in Professionals [a]	-0.207	0.000	***	-0.192	0.000	***
% people in sales, services and office occupations.	0.181	0.000	***	0.193	0.000	***

[a] Professionals refer to those in management, business, science, and arts occupations
*** significant at 0.001 level; ** significant at 0.05 level; * significant at 0.1 level.

LISA (Local Indicator of Spatial Association) maps in Map 3 demonstrates the spatial correlation between stay-at-home index and infection rate, death rate, respectively. It shows not only the relations between each pair of variables, but also relations between census tracts and their neighboring census tracts. This spatial association results in four types of sub-regions: the high-high and low-low clusters (with positive local spatial autocorrelation) and the high-low and low-high clusters (with negative local spatial autocorrelation). For example, the high-high (low-low) clusters identified on the map are census tracts with high (low) stay-at-home index which are surround by tracts with high (low) infection/death rate. The high-low (low-high) subregions are tracts with high (low) stay-at-home index which are surround by tracts with low (high) infection/death rate. These maps allow us to identify clusters that indicate the effectiveness of staying at home (e.g. high-low clusters), but also regions that other factors may be shaping the infection and death that deserve further investigation.

Map 3 Bivariate LISA Map on Stay-at-home Index and Infection Rate, Death Rate





While correlation coefficients and LISA maps give powerful evidence for associations between infection and death rate and other indicators, they only measure bi-variate relationships, without considering/controlling other variables. Therefore a multi-variable regression model is necessary to better identify the relationship between pandemic outcomes and independent variables.

4) Poisson regressions demonstrate the importance of stay-at-home order and public transit system

Poisson regressions are adopted given the count nature of infections and deaths, which clearly demonstrate the significant roles of stay-at-home order and public transit system even after controlling various socioeconomic variables. According to Table 3, stay-at-home indicator has a significant and negative effect on both infection and death rate. This means the more time people spent at home (compared to the same period in 2019), the lower the infection and death rate for the census tract. With one percentage point increase in average time spent at home, the log likelihood of infection rate decreases by 0.005 and death rate decreases by 0.007. In other words, census tracts will have 0.5% fewer infections and 0.7% fewer deaths.

The number of MTA stations has a positive and significant effect on both infection and death rate. The more MTA stations a census tract has, the higher its infection and death rate are. With each additional stop, infection and death rates are expected to increase by 1.51% and 1.31% respectively. As the number of MTA stations is only an indirect measure for ridership, it is important for future studies to investigate the association between actual public transit ridership during this pandemic and the infection and death rates, respectively.

Table 3 Part of Poisson Regression Results (see Table A1 for full model results)

	Infection Rate				Death Rate			
Variables	Estimates	St. Error	P-value		Estimates	St. Error	P-value	
Stay-at-home	-0.005	0.000	0.000	***	-0.007	0.001	0.000	***
MTA stations	0.015	0.000	0.000	***	0.013	0.001	0.000	***

Other significant findings include the following (see appendix Table A1 for details):

- Census tracts with a larger share of Minorities, higher poverty rates, larger household size, more households living in overcrowding, larger share of people 60+ have higher infection and death rate.
- Census tracts with a larger share of college+ education, people taking public transit and people in sales, services and office occupations have lower infection and death rate.
- Census tracts with a higher share of people without health insurance have higher death rate (not infection rate).
- Census tract with larger share of Professionals, Blacks and Asians have lower infection rate (not significant for death rate).

While most findings on socioeconomic variables are as expected, two findings are somewhat puzzling.

First, %Minority has a positive and significant effect on both infection and death rate; yet, %Hispanics is not significant at all, and %Blacks and %Asians have significant but negative effects on infection rate only. In other words, a larger share of ethnic minorities does lead to higher infection and death rate. However, the share of a specific ethnic group (%Blacks, % Asians, % Hispanics) does not. In contrast, census tracts with a higher share of Blacks and Asians have lower infection rate. While the Spearman correlation coefficients indicate positive associations between %Blacks, %Hispanics and infections/death rates, Poisson regressions show otherwise when the other factors are controlled. This means the positive associations between share of a specific ethnic group and infections and deaths might be spurious, and they disappear after controlling other socioeconomic indicators, such as poverty rate and overcrowding as well as stay-at-home indicator and the public transit system.

Secondly, %people in sales, services and office occupation has negative effect on infection and death. This seems to be contrary to the perception of danger associated with sales and services occupations during the pandemic. However, this occupation category includes many different types of occupations sales, services, as well as office occupations, which is not equivalent to the essential work defined by the government for shutdown and makes it harder to draw specific conclusions. Detailed occupation categorization is needed for better understanding of the relationship between occupation and pandemic outcomes. It might also be the result of the stay-at-home, when most sales, service industries and office occupations are closed, leading to lower infections.

While Poisson regression gives us an overall relationship between explanatory variables and outcome variables, it is a non-spatial/global regression, which assumes the effects of indicators are the same across space. However, this assumption is not necessarily true, especially in infectious diseases when distance and location really matter. Thus we carry out additional spatial analyses as shown in the following section.

5) Spatial analyses demonstrate stay-at-home order and public transit system have spatially uneven effects on pandemic outcomes.

Considering the distance between locations as a key factor in pandemic outcomes, Geographically Weighted Regressions (GWRs) are conducted for both infection and death rate. According to percent deviance explained and AIC_c (Corrected Akaike Information Criterion, a method for setting bandwith in spatial search), GWRs are clearly better models than non-spatial models such as Poisson and Gaussian models (Table 4). GWRs reveal stay-at-home index, MTA stations, and socioeconomic indicators have spatially varied effects on infection and death rate across census tracts. The summary statistics for all GWR parameter estimates are listed in Appendix Table A2, and coefficients for key variables are mapped below.

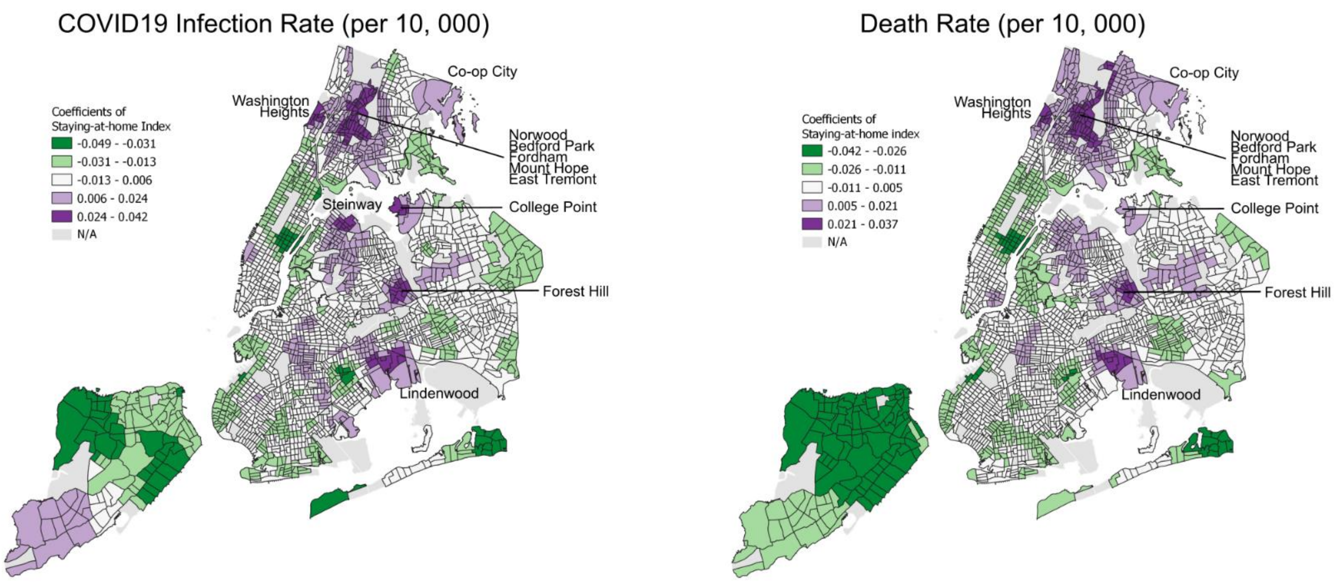
Table 4 Model Comparison

	nfection Rate			Death Rate		
	Gaussian	**Poisson**	**GWR**	**Gaussian**	**Poisson**	**GWR**
AIC:	20,817	98,823	19,153	10,701	16,518	3,884
AICc:	20,819	86,088	20,596	10,703	8,853	4,436
R^2/ %deviance explained:	0.089	0.145	0.828	0.087	0.132	0.741
Adj. R^2/ %deviance explained:	0.083	0.139	0.691	0.08	0.126	0.628

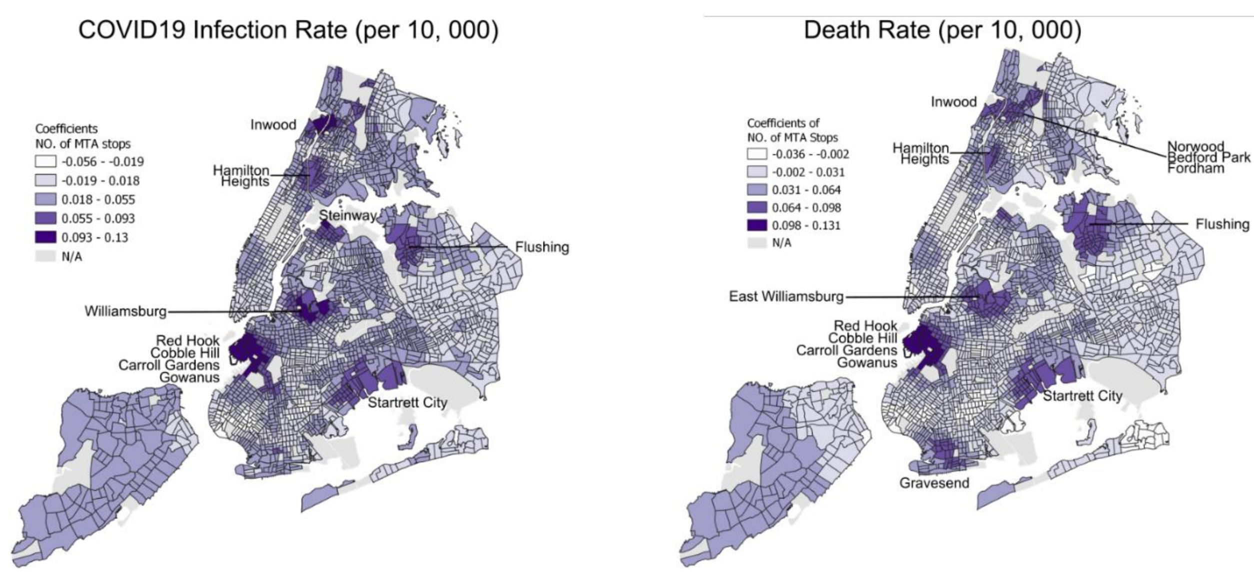
Map 4 – 9 show that stay-at-home index, MTA stations, and resident profiles such as ethnic compositions and age structure all have spatially varied effects on infection and death rate, and their patterns are all somewhat different. GWRs results reveal the high impact areas for a specific factor (e.g. %Blacks), which allow us to identify the most vulnerable neighborhoods within the city for this particular factor, for targeted and high impact policy intervention.

According to Map 4, coefficients for stay-at-home index vary significantly across space for both infection and death rate. For most census tracts, the coefficients are negative (green on the map), indicating more time spent at home leads to lower infection and death rates, demonstrating the effectiveness of stay-at-home order. The lowest negative coefficients (dark green) are mostly in the north half of Staten Island, Upper East Side and Midtown in Manhattan, and Far Rockaway area in Queens. In other words, these census tracts benefit the most from staying at home. However, in quite some census tracts, the coefficients are positive (purple color on the map), meaning more time spent at home are correlated with higher infection and death rate. The highest positive coefficients are in central Bronx (e.g. Norwood, Bedford Park, Fordham, Mount Hope, and East Tremont), Brooklyn (e.g. Spring Creek and Lindenwood) and Queens (e.g. Astoria, Steinway, College Point, and Forest Hills). In other words, spending more time at home in these census tracts somehow is associated with higher infection and death rate. In addition to the lack of effectiveness of stay-at-home order, this demonstrates other factors outperform staying at home shaping pandemic outcomes in these census tracts. For example, in the Forest Hills neighborhood in Queens, we found that the percentage of the elderly population is very high (ranging between 33.5% and 50.9%), which likely outperforms the stay-at-home index. Analysis like GWR help researchers to locate areas of a particular pattern and further identify the underlying factors that contributes to the infection and death rates.

Map 4 GWR Coefficients for Stay-at-home Index for Census Tracts

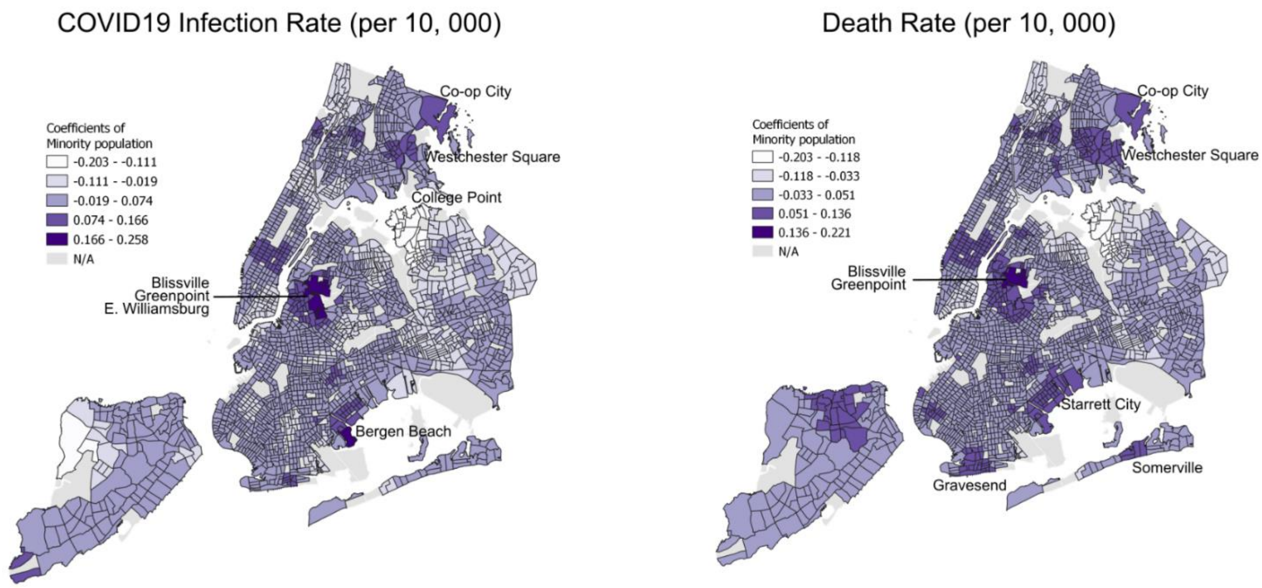


Map 5 GWR Coefficients for MTA Stations for Census Tracts



Similarly, coefficients for MTA stations vary significantly across census tracts (Map 5). They also range from negative to positive. In census tracts with darker color, MTA stations have a larger positive effect on infection and death rate. These high coefficient clusters are mainly in Red Hooks, Williamsburg and Starrett City in Brooklyn, Steinway, Howard Beach and Flushing in Queens, Inwood in Bronx, where a larger number of MTA stations are associated with higher infection and death rate. With relatively a small number of subway stations in each census tract, MTA stations are mostly bus stops. These high impact areas are also neighborhoods with fewer subway lines/stations that heavily rely on buses for transport. These correlations show the potential connections between actual ridership and infection and death, which should be further investigated.

Map 6 GWR Coefficients for Percent of Minority Population

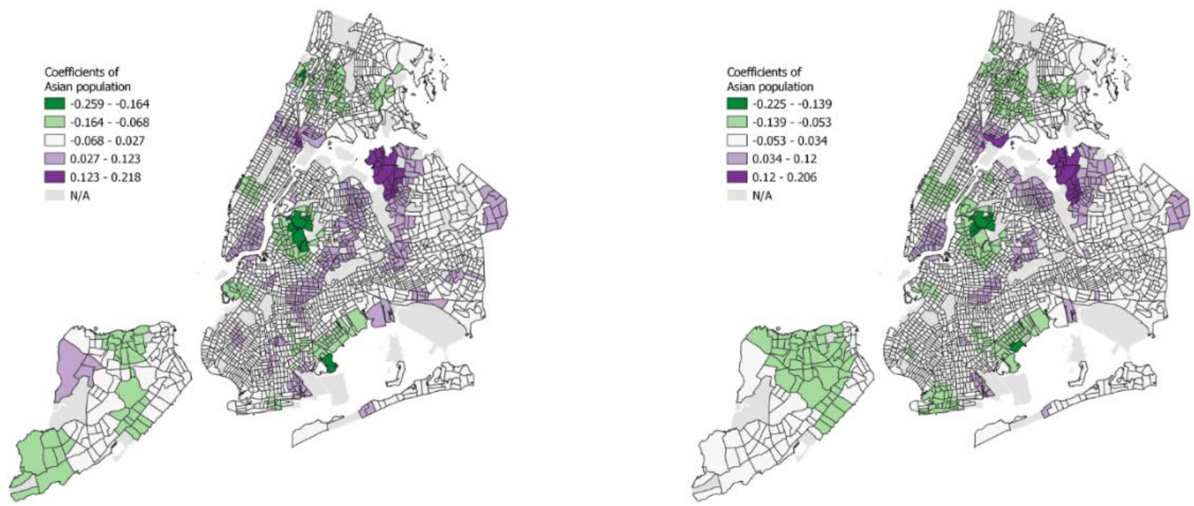


Map 6 shows the uneven impact of percent minority population on infection and death rate. Census tracts with darker purple colors have positive coefficients, meaning higher %Minority leads to higher infection and death rates. The highest positive coefficients are in East Williamsburg and Bergen Beach in Brooklyn and Blissville in Queens. Positive coefficients are also found in Midtown/Upper East Side in Manhattan, Co-op city and Westchester Park in Bronx, Brownsville, Brighten Beach and Canarsie in Brooklyn, as well as North end of Staten Island (for death rate). Interestingly, %Minority has negative effect on parts of the city, where a higher concentration of minorities is associated with lower infection and death rate such as Flushing in Queens and Lower Eastside in Manhattan. Map 7-8 further investigate the impact of a specific ethnic group.

Coefficients for %Asians are displayed in Map 7. Purple colors indicate census tracts with positive coefficients, meaning higher infection and death rate in census tracts with higher percent Asians. The highest positive coefficients are located in Flushing, Queens and Mott Haven in Bronx, and smaller and positive coefficients are also located in Lower East Side/Chinatown/Lower Manhattan and East Harlem in Manhattan, Jackson Heights/East Elmhurst/Corona in Queens and various parts in Brooklyn. These high impact neighborhoods mostly correspond to the high concentration of Asian population. However, in other census tracts, there is a negative association with a higher concentration of Asians associated with lower infection and death rate, such as those in Midtown in Manhattan, much of Staten Island and some areas in Bronx, Brooklyn and even Queens.

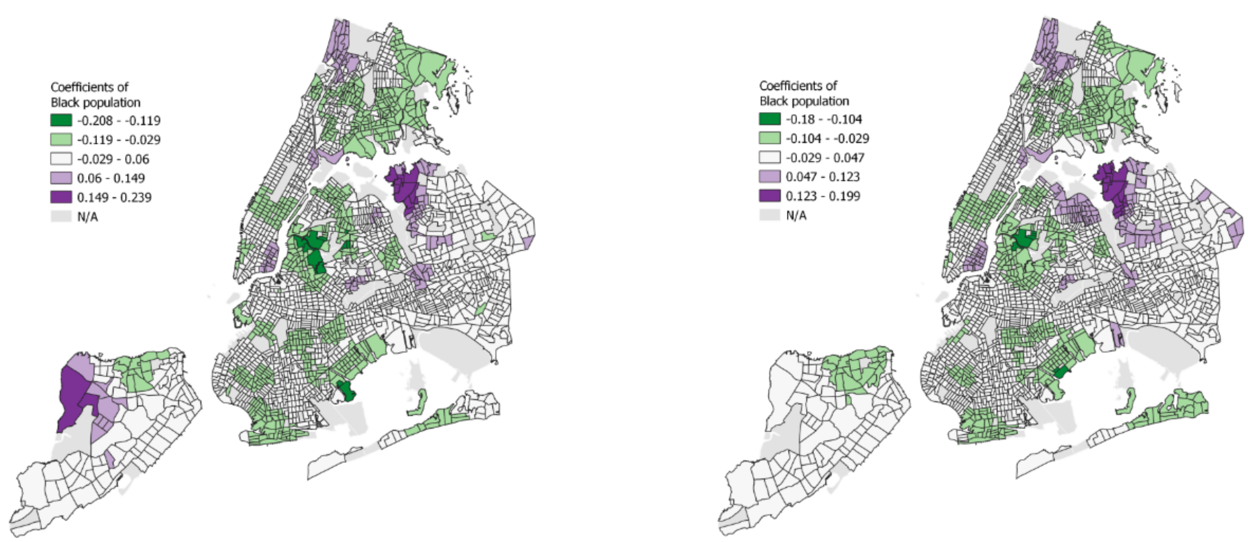
Map 7 GWR Coefficients for Percent Asians for Census Tracts

COVID19 Infection Rate (per 10, 000) Death Rate (per 10, 000)



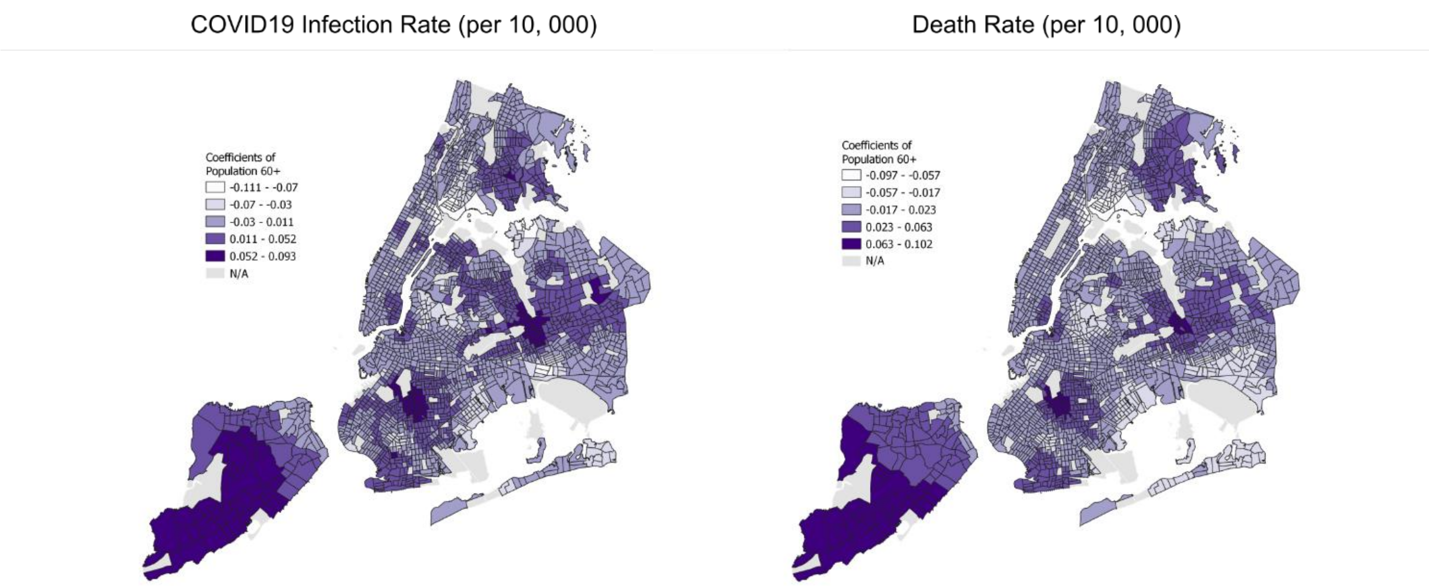
Map 8 GWR Coefficients for Percent Blacks for Census Tracts

COVID19 Infection Rate (per 10, 000) Death Rate (per 10, 000)



According to Map 8, while %Blacks has positive effects on infection rate in parts of Staten Island, Queens, Bronx and lower east side in Manhattan, its effect is much more significant and widespread for death rate. There are many more census tracts with the highest positive coefficients for death rate, which are mostly in Queens (College Point/Flushing), but also in the northwest side of Staten Island, Manhattan (the Lower East Side, Chinatown and Little Italy, Harlem), the northwestern corner of Bronx (e.g. Riverdale). Again, throughout NYC, there are census tracts with negative coefficients for both infection and death rate, where a higher concentration of Blacks is associated with lower infection and death rate, such as the north end of Staten Island, Midtown/Upper East Side in Manhattan, the south end of Brooklyn, as well as parts of Queens and Bronx.

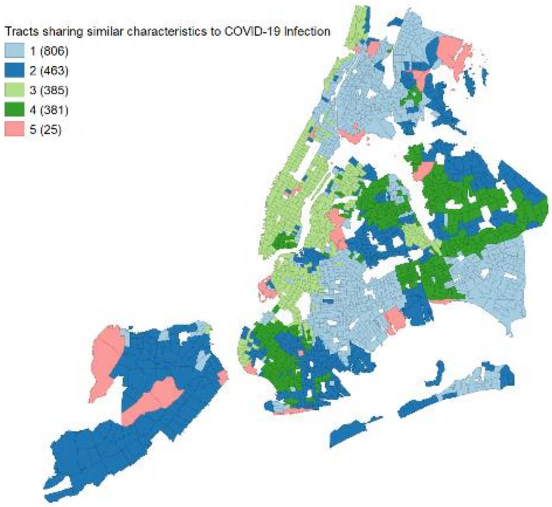
Map 9 GWR Coefficients for Percent of Population Aged 60+

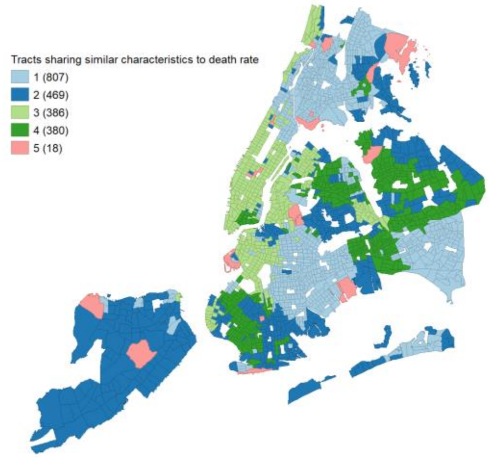


Map 9 displays coefficients for Percent of Population Aged 60+. Again, there is huge spatial variations, with both negative and positive effects. The highest positive effects are in much of Staten Island, central Brooklyn (e.g. Prospect Park, Ditmas Park, and flatbush), Queens (e.g. Forest Hills Gardens, Richmond Hill, and Kew Gardens) and the eastern Bronx, where census tracts with a higher percentage of elderly population have higher infection and death rate.

In addition to the factor-specific clusters identified in above maps, K-means Cluster Analysis is conducted with pandemic outcomes and all significant variables identified in the Poisson regression models. We generate five clusters with similar characteristics among census tracts (Map 10). We may consider these are "New Five Boroughs" based on COVID19 infection and death rate, as well as other identified significant characteristics in census tracts. While most census tracts in each borough are similar and in the same cluster, there are census tracts differ from nearby census tracts, and share similarities with those far away. For example, a few census tracts in Mid-town Manhattan (in Cluster 5, salmon color) are very different from other tracts in Manhattan, and instead they are similar to some census tracts in the other four boroughs. Clusters are slightly different for infection and death rate. Census tracts in Cluster 5 have extremely high infection and death rate, unusually high number of MTA stations, and much lower stay-at-home time than the other four clusters. This allow us to identify census tracts that are significantly different from surrounding census tracts, conduct further investigation and apply localized policy interventions.

Map 10 K-means Cluster Analysis: New Five Boroughs





Policy Implications

This preliminary research can offer at least the following three policy implications.

First of all, stay-at-home order has worked in most census tracts. The more time people spent at home (compared to the same period in 2019), the lower the infection rate and death rate at the census tract level. As we enter the second wave of COVID-19, the local government should implement strict stay-at-home order, and encourage people to spend as much time at home as possible. While a total lock-down as China implemented in Wuhan is probably impossible in NYC, the government can offer helps to make it easier for people to stay at home. Here are some examples of what the government can do to make stay-at-home order more effective:

- Offers free or subsidized high-speed Internet services and computers/IPADs to households and neighborhoods that do not have access.
- Requires employers to offer stay-at-home option and needed equipment to their employees such that non-essential workers can all work at home.
- Provide grocery delivery services to segments of population who do not know how to do online shopping such as the elderly
- Fines can be applied to people who are out for non-essential purposes.

For census tracts that stay-at-home order did not work, such as those in Staten Island, local investigations are needed to further understand why stay-at-home order has not worked there as in the rest of the city, which can lead to localized policy interventions.

Second, the public transit system increases infections and deaths. The more MTA station a census tract has, the higher the infection and death rate. Thus shutting down some MTA stations, especially bus stations which are more prevalent, will be effective in lower infection and death rate. This is especially important in census tracts in parts of Bronx, Brooklyn and Queens where MTA stations have the highest impact as identified in Map 5.

Third, high risk neighborhoods can be identified with high effect of %Minority and %Population 60+, as identified in Map 6 and 9, as well as Cluster 5 in Map 10. Instead of citywide stay-at-home order, interventions at finer scale within the city is needed, and neighborhood specific support (depending on the resident profile, such as concentration of minorities and elderly) should be provided to these high-risk neighborhoods.

Next Steps

This is the first step of our research. We will continue the research in the following ways:

1) Using actual subway turnstile ridership data to measure mobility reduction

SafeGraph cell phone data is based on available cell phone devises, which don't cover the whole population. For comparison, we will use the subway turnstile ridership data for each station released by MTA to measure mobility. Ridership for stations within each census tract is combined to measure the mobility for that census tract. Mobility reduction is measured by the ratio between ridership in a two-week period in 2020 and that in the same period in 2019.

2) Mobility infrastructure will be measured more systematically using an innovative method called "Space Syntax".

While the number of MTA stations used in this study measures the connectivity in each census tract, it measures only one aspect of the public transit system and mobility infrastructure. We will use an innovative method "Space Syntax" to better quantify the public transit system and urban mobility environment. Space Syntax is a general term for quantitative approaches of describing built environments (Bafna, 2003), which has been used to associate human behavior patterns such as group movement and individual wayfinding within built environments (Hölscher et al., 2012; Li & Klippel, 2016; O'Neill, 1992; Penn, 2003). We will adopt three measures in the Space Syntax family: *connectivity, integration,* and *complexity*, to quantify mobility environments defined by public transit networks.

a) Connectivity shows how paths such as subway and bus lines are connected in a space. A transit line that intersects with many other lines has a high connectivity.

b) Complexity is a measure based on intersections, point-based features such as transit stations (O'Neill, 1992). If a station is served by many subway and bus lines, its *complexity* is high, which will add more weights to complexity of the census tract where it is located.

c) *Integration* indicates the least number of "steps"/stations a person must travel to reach a destination.

We believe these three measures can better capture the connectivity of the public transit system than just the number of stations. They will be used in GWRs, replacing the number of

MTA stations, to determine the effect of the public transit system on infection and death rate, and we believe they can better predict infection and death rates.

In addition to the public transit system, mobility infrastructure in NYC includes the taxi system, airports (with both international and domestic flight), and regional trains. They need to be considered in pandemic outcomes as well when data is available.

3) Run the regression for every two-week period

Currently regressions are conducted with infection and death rate calculated with cumulative infections and deaths. The next step is to conduct regressions for every two-week period, with a two-week lag between mobility/stay-at home and infection and death rate. The two-week periods are chosen to be consistent with the stay-at-home order (starting from March 23rd) and later the four stages of reopening in NYC. This would allow us to assess whether the effects of stay-at-home order and public transit system change over time and how. This also allows us to assess how the stages of re-opening changed the effects of stay-at-home order and public transit system, as well as other factors such as the resident profile.

4) Simulations with different policy scenarios to find optimal lockdown policy

This research currently uses the actual mobility reduction resulted from the stay-at-home order. With the heated public debate on lockdown vs. reopening, pandemic outcomes will be simulated with different scenarios of mobility restriction policy. The possible lockdown policy ranges 0-100%, as “0” means there is no lockdown policy with no mobility reduction, and “100%” indicates a complete lockdown policy with 100% mobility reduction. Any number between 0-100 percent indicates a partial lockdown policy with some mobility reduction. Using above regression results, simulations on pandemic outcomes at the census tract level will be conducted with every 10% mobility increment for different degrees of partial lockdown.

The simulation results will demonstrate outcomes of different lockdown policies and help to identify the optimal lockdown policy with mobility reduction threshold for best pandemic outcomes. They can also help to identify most at-risk census tracts for tract-specific policy to minimize impact on vulnerable neighborhoods and populations. The results are particularly important in future epidemics and can help decision makers to develop appropriate prevention and mitigation policies to reduce health disparities and minimize infections and deaths.

5) Individual level analysis is needed to truly understand racial disparities in pandemic outcomes

While the simple bivariate correlation shows the positive associations between concentration of minorities and higher rates of infection and death in census tracts, spatial analyses show that the effects of %Blacks, %Asians and %Hispanics vary significantly across space, ranging from negative to positive. This means census tracts with higher percentages of Blacks and Hispanics do not necessarily always have higher infection and death rates. There are many other factors shaping pandemic outcomes. In addition, this finding is derived at the census tract level, and cannot be inferred to the individual level. In other words, this does not mean that Blacks and Hispanics are more or less likely to be infected or die. Rather, individual level analysis is needed to better answer the question whether Blacks and Hispanics are more likely to be infected and die in COVID 19 pandemic.

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Appendix

Table A1 Poisson Regressions on Infections and Deaths

	Model 1: Infections				Model 1: Deaths			
Variables	Estimate	SE	p-value		Estimate	SE	p-value	
Stay-at-home indicator	-0.005	0.000	0.000	***	-0.007	0.001	0.000	***
MTA stations	0.015	0.000	0.000	***	0.013	0.001	0.000	***
%Minority	0.007	0.001	0.000	***	0.006	0.003	0.036	**
%Black	-0.003	0.001	0.001	***	0.000	0.003	0.921	
%Asian	-0.007	0.001	0.000	***	-0.003	0.003	0.226	
%Hispanic	0.001	0.001	0.406		0.001	0.003	0.777	
% HHs with crowding (> one person per room)	0.001	0.000	0.001	***	-0.002	0.001	0.075	*
% people taking public transit	-0.007	0.000	0.000	***	-0.004	0.001	0.000	***
Household size	0.047	0.006	0.000	***	0.083	0.020	0.000	***
Poverty rate	0.000	0.000	0.088	*	0.003	0.001	0.001	***
% People with College+ education	-0.004	0.000	0.000	***	-0.004	0.001	0.003	***
% People aged 60	0.006	0.000	0.000	***	0.018	0.001	0.000	***
% People with no health insurance	0.000	0.001	0.832		0.009	0.002	0.000	***
% People in Professionals[1]	-0.005	0.001	0.000	***	-0.002	0.002	0.224	
% People in Sales, Services and office occupations	-0.013	0.001	0.000	***	-0.011	0.002	0.000	***
Intercept	-2.873	0.049	0.000	***	-6.203	0.169	0.000	***
Deviance:		86055			8821			
Log-likelihood:		-49395			-8243			
AIC:		98823			16518			
AICc:		86088			8853			
Percent deviance explained		0.145			0.132			
Adj.Percent deviance explained		0.139			0.126			

[1] Professionals refer to those in: management, business, science and arts occupations

*** significant at 0.001 level; ** significant at 0.05 level; * significant at 0.1 level.

Table A2 Summary Statitics for GWR Parameter Estimates for Infection and Death Rate

	GWR1: Infection Rate					GWR2: Death Rate				
Variable	Mean	STD	Min	Median	Max	Mean	STD	Min	Median	Max
Intercept	-3.435	3.54	-18.91	-3.803	10.787	-6.762	3.152	-16.506	-6.837	4.852
Stay-at-home indicator	-0.004	0.014	-0.049	-0.004	0.042	-0.004	0.013	-0.042	-0.004	0.037
MTA stations	0.026	0.027	-0.056	0.024	0.130	0.028	0.027	-0.036	0.025	0.131
%Minority	0.009	0.046	-0.203	0.005	0.258	0.010	0.043	-0.203	0.010	0.221
%Black	-0.006	0.045	-0.208	-0.003	0.239	-0.004	0.039	-0.180	-0.006	0.199
%Asian	-0.012	0.050	-0.259	-0.006	0.218	-0.011	0.046	-0.225	-0.009	0.206
%Hispanic	-0.006	0.046	-0.203	-0.004	0.191	-0.004	0.041	-0.180	-0.003	0.190
% HHs with crowding (> one person per room)	0.004	0.019	-0.057	0.002	0.084	0.002	0.017	-0.047	0.001	0.073
% people taking public transit	-0.009	0.013	-0.062	-0.008	0.042	-0.008	0.011	-0.045	-0.007	0.032
Household size	-0.020	0.540	-2.138	0.032	1.431	0.036	0.528	-1.954	0.038	1.638
Poverty rate	0.000	0.018	-0.067	0.000	0.087	0.000	0.015	-0.052	0.001	0.039
% People with College+ education	0.003	0.023	-0.092	0.003	0.083	0.005	0.025	-0.092	0.004	0.082
% People aged 60	0.006	0.029	-0.111	0.006	0.093	0.010	0.027	-0.097	0.008	0.102
% People with no health insurance	0.004	0.033	-0.123	0.004	0.176	0.006	0.029	-0.094	0.005	0.113
% People in Professionals[1]	-0.001	0.028	-0.127	0.000	0.126	0.004	0.027	-0.107	0.005	0.089
% People in Sales, Services and office occupations	-0.006	0.031	-0.163	-0.005	0.141	-0.003	0.028	-0.120	-0.001	0.075
Effective number of parameters (trace(S)):		910				628				
Degree of freedom (n - trace(S)):		1,150				1,432				
Deviance:		17,332				2,628				
AIC:		19,153				3,884				
AICc:		20,596				4,436				
BIC:		24,277				7,420				
Percent deviance explained:		0.828				0.741				
Adj. percent deviance explained:		0.691				0.628				
Adj. alpha (95%):		0.001				0.001				
Adj. critical t value (95%):		3.331				3.226				