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COVID-19 pandemic and minority health disparities in New York City: A spatial and temporal perspective

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Abstract

New York City (NYC) was the epicenter of COVID-19 pandemic for a long time, and the government introduced a city-wide lockdown policy to mitigate the spread of virus. Minority communities, however, suffered disproportionally high percentage of infection and mortality rates, a disturbing phenomenon that deserves scrutiny. Adopting a spatial and temporal perspective, this study aims to investigate health disparities in this pandemic by focusing on mobility in the city. Considering both public transit and the lockdown policy essential factors that impact infection and mortality, this study introduced a measure indicating mobility-restricted transit as the spatial factor. Additional factors include ethnic minorities based on their nativity and three categories of social vulnerability: socioeconomic status, household composition, and housing type. This study selects eight phases, each of which consists of 2 weeks to derive infection and mortality rates to investigate the impacts of those factors. As infection and mortality data are published based on ZIP code, this study further estimates the infection and mortality rates at a finer level of census tract through spatial apportionment. Results reveal the significant impact of mobility-restricted transit on both infection and mortality and show certain clusters of neighborhoods being highly impacted. In addition, this study identifies neighborhoods where native-born and foreign-born of each ethnic minority (Blacks, Hispanics, and Asians) have high risk of infection and mortality. Through a spatial and temporal perspectives, this study identifies the complexity of patterns in minority health disparities in COVID-19 pandemic, which can inform policy makers for localized support to vulnerable neighborhoods to alleviate minority health disparities.

Keywords

Mobility restriction, lockdown, minority health disparities, public transit, nativity, COVID-19

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Introduction

New York City (NYC) is one of the most diverse cities in the world, with large minority communities with significant health and socioeconomic disparities. It quickly became the epicenter of COVID-19 pandemic in early 2020 (Higgins-Dunn, 2020). Studies suggest that counties with large population of racial and ethnic minority are prone to high infection and mortality rates (Lee et al., 2021; Yancy, 2020). There is a growing body of literature on minority health disparities in COVID-19 pandemic. However, most research focuses on county or state level. (see Dalsania et al., 2021; McLaren, 2021; Paul et al., 2021). Research on intra-city is very limited probably due to data limitation. This study aims to examine the patterns of health disparities within NYC at a finer spatial scale and uncover their social and spatial driving forces.

Different research has suggested many factors that contribute to COVID-19 infection and mortality among population. First, mobility restriction, implemented as stay-at-home order, is a policy applied as a nonpharmaceutical method to slow down the spread of the virus. Many studies suggest human mobility as a main factor contributing to the transmission of the virus (Buckee et al., 2020; Chang et al., 2021; Kraemer et al., 2020; Linka et al., 2021). Second, other studies suggest long-standing systemic socioeconomic and environmental inequalities are the factors placing these communities of colors at higher risk of being affected by COVID-19 (Lee et al., 2021). Third, sociologists suggest the COVID-19 mortality is affected by the concentration of minority population based on their nativity (i.e., native- or foreign-born) as a result of residential segregation (Friedman and Lee, 2021). While mobility restriction is announced at the city or state level, many minority residents, who work in essential business, still have to commute using public transit (Do and Frank, 2021; McLaren, 2021). It is then necessary to use a finer spatial scale such as census tract to understand how the mobility restriction policy, actual mobility, racial and social factors shape the disparities at the neighborhood level.

Therefore, this study investigates the impacts of mobility restriction, public transit, and minority nativity on both COVID-19 infection and mortality in NYC at the census tract level. As mobility restriction has evolved in New York over time with gradual reopening, this study then selects four successive phases after the lockdown policy was implemented, and another four phases after the mobility restriction policy was gradually lifted. The specific goal is to understand how the mobility restriction policy, reflected in public transit mobility, racial, and social factors shape health disparities in each phase. The findings can contribute to a better understanding of spatial disparities of minority health and provide valuable input for policy makers to introduce community-specific, localized policy and support.

Background

Health disparities in the COVID-19 pandemic

Research shows that minority groups are disproportionally impacted by this pandemic. According to the 2019 American Community Survey (ACS) (U.S. Census Bureau, 2020a), about 5.7 million residents live in NYC are minorities. For example, Black and Hispanic populations are about 1.5 times more likely to contract the virus, about 4 times more likely to be hospitalized, and about 3 times more likely to die from COVID-19–related symptoms than non-Hispanic White population (CDC, 2020). Other research points out that many Blacks and ethnic minorities live in crowded space in poor neighborhoods with limited access to healthy food, which may all push minority health disparities to a more disproportional level (Yancy, 2020). In addition, these populations are about 2.1 times higher than non-Hispanic White population in mortality rate (Do and Frank, 2021).

Transit network

Spatial factor such as transit network is critical to the transmission of infectious diseases. Studies have suggested that the high mortality due to COVID-19 in minority communities can be mostly related to the use of public transit, which they significantly rely on for commuting due to their income level and financial insecurity (McLaren, 2021). Since NYC has the largest subway network in terms of the number of stations (CityMetric, 2015), studies suggest that the massive subway system in NYC is a main platform of transmitting the virus at the beginning of the pandemic, which have accelerated the infection in NYC (Carrión et al., 2021; Harris, 2020). Although the ridership has reduced dramatically during 2020, the Metropolitan Transportation Authority (MTA) still reported 0.64 billion subway ridership and 0.38 billion bus ridership in 2020, which was 31% and 50% of its ridership on subway and bus in 2019, respectively (MTA, 2021). In addition, MTA has stopped subway service overnight during the pandemic to sanitize all trains, but more buses have been added to schedules to accommodate the need of commuters in early morning (Rose, 2020). Therefore, this study aims to consider mobility in both subway and bus transit when deriving the spatial factor.

Mobility restriction

Mobility restriction, implemented as the lockdown policy, has been widely executed around the world as an essential nonpharmaceutical approach to diminish the spread of virus. Many employees have switched to work from home since March 2020 in New York. Researchers compare the mobility restriction in multiple cities and suggest that the effect of mobility restriction varies among cities. For example, according to Glaeser and colleagues (2020), mobility restriction has a great effect on reducing the infection in NYC, but not so in Atlanta when the pandemic just began. This may be due to the fact of a larger population in NYC.

Another factor contributing to the varying effects may be the reliance on public transit for commuting. While many employees started to work from home, essential workers were still required to work in person. A large portion of essential workers are those living in communities with lower socioeconomic status and higher percentage of minorities. In Chicago, researchers report that the city-wide mobility dropped substantially after the execution of mobility restriction, but the mobility of poor neighborhoods did not change much at the beginning as their trips to essential business remain frequent (Chang et al., 2021). It is likely that residents from these neighborhoods still need to work in places such as grocery stores. New York City shows a very similar pattern of intra-city disparities in mobility (McLaren, 2021). Using tracked mobile phone data provided by SafeGraph (2020), studies have reported that neighborhoods with high proportion of Blacks or Hispanics maintain high mobility within the city (Tanguay and Lachapelle, 2020). In the meantime, residents living in high-income neighborhood can benefit from working from home or even leave the city to places outside the city (Valentino-DeVries et al., 2020). Therefore, the requirement of commuting to work in-person for essential business, intervened with the poorer socioeconomic status and pre-existing health conditions, may all further intensify infection and death within minority communities.

In short, it is important to address the spatial factor of public transit in the study of minority health minorities as a virus is airborne. Some of the studies consider the spatial factor at larger spatial scale because most published data of COVID-19 are at county or ZIP code level. Using a finer spatial scale such as census tract can reveal more details on minority health disparities. Furthermore, the universal lockdown policy is executed very differently as mobility varies within a city. Communities with higher proportion of Blacks or Hispanics still need to commute to work in essential business. In addition, because of the large portion of foreign-born population in NYC, nativity of ethnic minorities shows a different association with COVID-19–related mortality (Friedman and Lee, 2021). Therefore, this study aims to combine spatial, racial and social factors in understanding their impacts on COVID-19 infection and mortality at the level of census tract in NYC. To understand the change of disparities over time, this study investigates the infection and mortality in eight phases to shed light on how the mobility restriction influence infection and mortality rates in a particular phase.

Data and methods

To calculate the *mobility restriction*, this study uses aggregated mobility data provided by SafeGraph (2020). Since this pandemic, researchers have suggested the use of aggregated mobility data as a valuable way to investigate the effect of mobility restriction policy and public responses (Buckee et al., 2020). SafeGraph collects and aggregates about 10% of 45 million mobile devices in U.S. to represent the foot traffic patterns (SafeGraph, 2019). Data bias is a concern among researchers as it is not a comprehensive collection of the entire population. The company itself has carried out assessment of sampling, which showed high correlation with U.S. Census data (SafeGraph, 2019). A recent study carried out in Yellowstone National Park compares the SafeGraph data with actual park visitation statistics and shows the validity of using SafeGraph data for monitoring foot traffic (Liang et al., 2021). The particular SafeGraph dataset used in this study aggregates daily movement of sampled cellphone users at the level of census block group in 2019 and 2020. This study uses the average time staying at home in 2020 and compares it with the corresponding period in 2019 to generate the measure for mobility restriction.

To understand health disparities from a temporal perspective, this study selects eight phases for data collection. New York State executed the lockdown policy since late March 2020 and then gradually reopened since June 2020. Thus we select four phases since the beginning of the lockdown and four phases since the beginning of gradual reopening. Considering the incubation period of COVID-19 virus at the beginning of the pandemic, each phase consists of 2 weeks. This study follows the findings of Qin et al. (2020) and uses COVID-19 infection and mortality data 14 days following each phase to reflect the actual effect of the mobility restriction of each phase. Table 1 shows the dates of each phase and the corresponding periods of retrieved COVID-19 data.

New York City's five boroughs, including Manhattan (New York County), Brooklyn (King County), Queens (Queens County), Staten Island (Richmond County), and Bronx (Bronx County), are the study areas (hereafter NYC). New York City is the early epicenter with more confirmed infection and mortality than other cities until mid-2020 (Thompson et al., 2020). Many factors contribute to this unprecedent outcome. First, the heavy reliance on public transit in NYC potentially accelerates the infection. Before the pandemic, the ridership in NYC was 1.7 billion on subways and 0.68 billion on buses (MTA, 2021). Although the ridership dropped substantially since the pandemic, 31% of the 2019 subway ridership and 50% of the bus ridership remained in 2020. The ridership is likely related to the demand of residents working in essential business, to whom the mobility restriction, is not applicable. The mobility restriction policy only applies to employees

Table 1. Chosen phases of mobility restriction and corresponding phases of COVID-19 data collection.

	Phase 1	P2	P3	P4	P5	P6	P7	P8
Mobility restriction	Mar 23–Apr 05	Apr 06–Apr 19	Apr 20–May 03	May 04–May 17	Jun 08–Jun 21	Jun 22–Jul 05	Jul 06–Jul 19	Jul 20–Aug 02
COVID-19 data	Apr 06–Apr 19	Apr 20–May 03	May 04–May 17	May 18–May 31	Jun 22–Jul 05	Jul 06–Jul 19	Jul 20–Aug 02	Aug 03–Aug 16

working in non-essential business but not those who have to work in essential business and rely on public transit. Although only subway turnstile data is available to calculate the actual ridership, it is important to note that bus ridership (0.38 billion) is still over 50% of subway ridership (0.64 billion) in 2020. It is necessary to consider the ridership on buses, as well as subways, to count for the mobility in public transit.

To estimate the ridership during a particular phase, this study introduces the measurement of MTA *station demand* to approximate the possible ridership before lockdown, as public transit stops are designed in theory to meet demand in the community (MTA/New York City Transit, 2018; Yu and He, 2017). This demand calculates the number of MTA bus and subway stations per 10, 000 residents in each census tract. This density is then weighted with actual mobility restriction measure for a particular phase to estimate the actual demand of public transit during the pandemic. This study uses the average time spent at home in 2019 as the basis, which is divided by the difference of stay-at-home time between 2020 and 2019 to calculate the stay-at-home ratio. The difference of this stay-at-home ratio from one indicates the mobility with restriction. For example, a 0.4 stay-at-home ratio indicates 60% of out-of-home mobility in a census tract comparing to the same period in 2019. This calculated mobility with restriction of each phase is applied as weight to the MTA *station demand* to indicate the *mobility-restricted transit* during this pandemic in each phase. The equation below shows the calculation

$$mobility\,restricted\,transit = station\,demand\,density * \left(1 - \frac{2020\,time\,at\,home - 2019\,time\,at\,home}{2019\,time\,at\,home}\right)$$

For the social factor, this study adapts the social vulnerability index (SVI) published by Centers for Disease Control and Prevention (CDC/ATSDR, 2018). This study adapts the remaining three categories of *socioeconomic status*, *household composition*, and *housing type/transportation* as the three categories of social factor in analyses. As the nativity of ethnic minority provides more details than SVI's category of *minority status and language*, this category is excluded.

For the racial factor, this study uses the minority's nativity from U.S. Census Bureau. Using ACS 2014–2018 5-year estimate (U.S. Census Bureau, 2020b), this study calculates the percentage of minority nativity in the categories of native-born (NB) and foreign-born (FB): Blacks (NB), Blacks (FB), Hispanics (NB), Hispanics (FB), Asians (NB) and Asians (FB). Since SVI is based on 2014-2018 ACS 5-year estimate, this study derives all demographic variables from the same ACS data, instead of more recent estimates.

This study retrieves infection and mortality cases for each phase from NYC Department of Health (2020). Because the COVID-19 data is only available at the ZIP code level, this study adapts the theory of spatial apportionment using land area of intersected and overlapping census blocks and ZIP Code Tabulation Area (ZCTA) to estimate the cases at the census tract level. From the field of public health, using ZIP code level data raises concerns of spatiotemporal mismatch as ZIP codes may not match to census derived ZCTAs (Krieger et al., 2002). Researchers evaluate different methods such as using land area or population using clinical data from four states and suggest the validity of its methods for apportion ZIP code level data to census tract level (Hibbert et al., 2009). Considering the high population density across entire NYC, this study adapts the land area as the weight to estimate the ZIP code level COVID-19 infection and mortality data to census tract level. These estimated cases are then used to calculate infection and mortality rates for each phase for each census tract. Since NYC did not start providing ZCTA-based mortality data until April 2020, the COVID-19 data contains only infection rates in the first three phases and both infection and mortality rates in the remaining five phases.

Analytical framework

Using COVID-19 estimates at census travel level as dependent variables, this study employs the *mobility-restricted transit*, *minority nativity*, and the three categories of *SVI* as key factors to investigate their impacts on health outcomes in each phase. As COVID-19 is airborne, the proximity to locations is crucial to the transmission which shapes spatial disparities. Therefore, this study utilizes geographically weighted regression (GWR) to determine how the aforementioned factors are associated with the COVID-19 outcome across all census tracts. Geographically weighted regression takes the variations across space into account, instead of assuming universal changes across space as in a linear regression. Geographically weighted regression integrates spatial heterogeneity which allows local variations of predictors (Fotheringham et al., 2003). This method has appeared in studies among different fields including crime analysis (Andresen et al., 2021), epidemiology (Mao et al., 2018) and in particular COVID-19 studies in various countries or regions (Huang and Li, 2022; Liu et al., 2020; Middya and Roy, 2021; Urban and Nakada, 2020). Urban and Nakada (2020) compare the effectiveness of multiple models including ordinary least square (OLS), spatial lag model (SLM), spatial error model (SEM), GWR, and multi-scale GWR (MGWR), and suggest the similar effectiveness between GWR and MGWR. They hence suggest GWR for more detailed assessment at the local level. Adapting this approach, researchers further compare the different model types (Gaussian vs Poisson) for regression and suggest the use of Gaussian and GWR model options (Huang and Li, 2022), which this study adapts.

Results

Descriptive statistics

At the city level, the first three phases show extremely high infection rates, which is over 600 out of every 100, 000 residents, reaching the peak in Phase 3 (Figures 1 and 2). Starting from Phase 4, infection rate drops substantially to under 100 per 100,000 residents and remains low in following phases. As mentioned earlier, there are no mortality data for Phase 1–3. In Phase 4 and 5, the city loses about five out of every 100, 000 residents in each phase, which is about 1000 residents in the entire city. After Phase 5, mortality rate drops to below one per 100, 000 residents. It is clear that the peak and the decline in mortality rate lagged behind infection rate.

While the city-level rates especially the mortality rates seem relatively low, the rates at the census tract level show large disparities across the city. Very high mortality rates disproportionally exist in neighborhoods where many minority residents reside. Figure 2 shows the mortality rate in Phase 4 as an example. While the city-wide mortality rate is below five per 100, 000 residents, 45 census tracts have cases 10 times higher than the city average. Twelve census tracks have cases 20 times

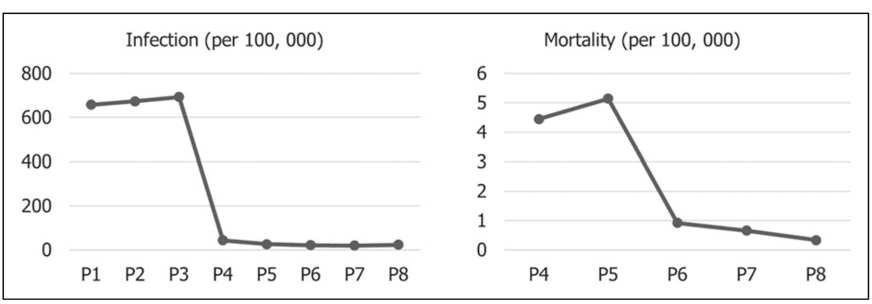

Figure 1. Infection rate and mortality rate in each phase at the city level.

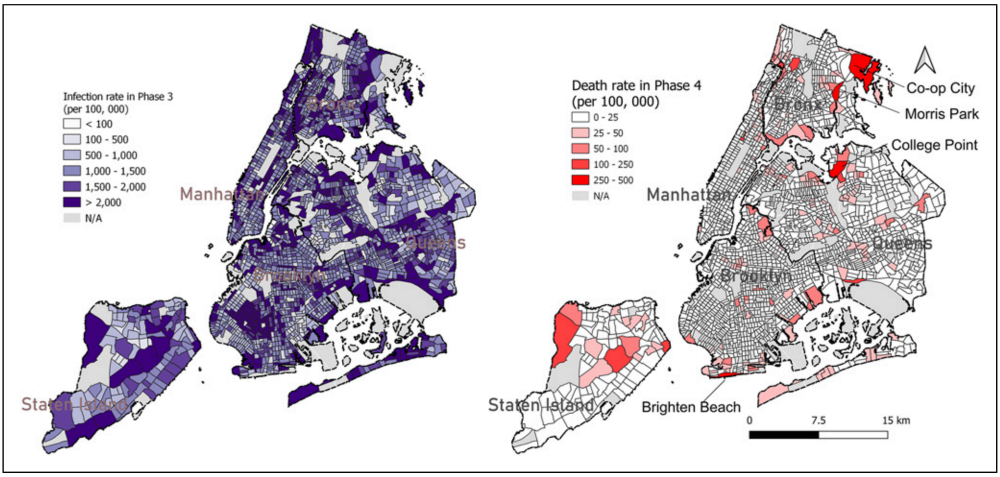

Figure 2. Estimated infection rate in Phase 3 and mortality rate in Phase 4 at census tract level.

Table 2. Descriptive statistics of derived variables.

	Mean	Std. Deviation	Min	Max
Mobility-restricted transit (per 10, 1000 population)	1.753	3.715	−0.593	122.900
Blacks (NB) %	16.708	19.032	0.000	75.878
Blacks (FB) %	0.087	0.126	0.000	0.679
Asians (NB) %	4.206	4.809	0.000	28.008
Asians (FB) %	0.101	0.127	0.000	0.758
Hispanics (NB) %	16.431	13.396	0.000	67.568
Hispanics (FB) %	0.108	0.113	0.000	0.617
SVI: Socioeconomic status	0.598	0.275	0.001	1.000
SVI: Household composition	0.439	0.297	0.004	1.000
SVI: Housing/Transportation	0.632	0.268	0.005	1.000

higher than the city average and four census tracks have cases 50 times higher than the city average. These neighborhoods are Co-op city and Morris Park in Bronx, Brighten Beach in Brooklyn, and College Point in Queens. This pattern of disparities across space further indicates the necessity of investigating the impacting factors which shape such disparities.

Besides the infection and mortality rates, other derived variables also show large variations within the city. As Table 2 shows, it is not surprising to find some census tracts with no Blacks (NB) or Hispanics (NB) at all, but some census tracts have over 75% Blacks (NB) or 67% Hispanics (NB). Similarly, while the average mobility-restricted transit is 1.75 per 10, 000 population, the highest mobility-restricted transit is over 122 per 10, 000 population.

Table 3 presents the results of Spearman correlation between infection rate and factors in each phase. The only significant factor that correlates to the infection in every phase is the mobility-restricted transit. The correlation of other factors such as the nativity and SVI vary phase by phase. For example, in Phase 1, the SVI of socioeconomic status and housing/transportation are negatively associated with infection rate. At the beginning of the lockdown period, there was likely still mobility exercised by large groups of residents. Negative correlation also exists between infection rate and both Asians (NB) and Asians (FB). Blacks (NB) are positively correlated with infection rate

Table 3. Spearman correlation of infection rate and factors in each phase at the census tract level.

Infection rate	P1	P2	P3	P4	P5	P6	P7	P8
Mobility-restricted transit	0.53**	0.683**	0.715**	0.51**	0.587**	0.804**	0.672**	0.636**
Blacks (NB)	0.026	0.027	−0.018	0.048**	0.052**	0.028	−0.013	−0.002
Blacks (FB)	0.001	0.001	−0.049**	0.029	0.027	−0.013	−0.041	−0.507**
Asian (NB)	−0.061**	−0.026	0.002	−0.031	−0.051*	0.04	0.002	0.02
Asian (FB)	−0.093**	−0.036	−0.018	−0.036	−0.035	0.025	−0.009	−0.003
Hispanics (NB)	0.049**	0.061**	0.004	0.021	0.136**	0.022	0.069**	0.108**
Hispanics (FB)	−0.029	0.007	−0.025	0.02	0.075**	0.002	0.025	0.055**
Socioeconomic status	−0.048**	0.02	−0.023	0.051**	0.008**	0.026	0.008	0.059**
Household composition	0.002	0.017	−0.04	0.034	0.058**	−0.025	−0.013	0.015
Housing/ Transportation	−0.068**	−0.006	0.03	0.005	0.065	0.039	0.038	0.064**

** $p < .05$.
* $p < .1$.

in Phase 4 and Phase 5. Blacks (FB), however, exhibit negative correlation with infection in Phase 3 and 8. Similarly, Hispanics (NB) population are positively correlated with infection rate in Phase 1, 2, 5, 7, and 8. Hispanics (FB) also exhibit positive correlation with infection rate but only in Phase 5 and 7.

The correlation between mortality rate and other variables in each phase show slightly different patterns (Table 4). In Phase 7 none of the factors is significantly correlated with the mortality rate. The mobility-restricted transit remains positively correlated with mortality rates in all other phases including Phase 4, 5, 6, and 8. Blacks (NB) are positively associated with mortality rate in Phase 5, but Blacks (FB) are not correlated with mortality rates in any phase. Hispanics (NB and FB) are positively correlated with mortality rate in Phase 4, but negatively associated with mortality rate in Phase 5. In summary, mobility-restricted transit shows positive association with mortality, which is consistent over time. However, minority nativity and SVI demonstrate complex relationships with mortality, whose patterns change over time.

Global regression

For each phase, both global regression and GWR are carried out in software MWGR 2.2 (Oshan et al., 2019). The independent variables include spatial, racial, and social factors. The model comparison between global regression and GWR are reported in Table 5. For global regressions, while adjusted R^2 for infection rate models is decent in each phase, adjusted R^2 for mortality rate models is very low. This is likely due to the much lower mortality rates in later phases, which result in only a few census tracts with mortality rates. In GWRs for infection rates, the lowest R^2 is 0.674 (Phase 4) and the highest is 0.890 (Phase 5). In GWRs for mortality rates, the lowest R^2 is 0.514 (Phase 6) and the highest is 0.763 (Phase 5). It shows that GWRs perform better than global regressions.

The global regression models show the *mobility-restricted transit* remains a significant positive factor in all phases and is the only factor that is robust and consistent over time (Table 6). This provides strong support that mobility is a key spatial factor that impacts the infection rate. While the factor is an estimate of potential ridership weighted by the actual mobility of residents within each 2-

Table 4. Spearman correlation of mortality rate and factors in each phase at the census tract level.

Mortality rate	P4	P5	P6	P7	P8
Mobility-restricted transit	0.197**	0.095**	0.098**	0.028	0.058**
Blacks (NB)	−0.007	0.151**	0.036	0.017	−0.018
Blacks (FB)	−0.037	0.156	−0.13	−0.003	−0.016
Asians (NB)	−0.023	0.038	0.007	−0.038	0.05**
Asians (FB)	0.003	0.054*	−0.011	−0.025	0.02
Hispanics (NB)	0.074**	−0.086**	0.022	0.03	0.015
Hispanics (FB)	0.048**	−0.07**	−0.011	0.01	0.002
Socioeconomic status	0.018	−0.041	0.009	0.038	0.003
Household composition	0.036	0.038	0.045**	0.041	0.025
Housing/Transportation	0.059**	−0.188**	0.008	0.039	−0.007

** $p < .05$.
* $p < .1$.

Table 5. Model comparison between global and local regression (GWR) in each phase.

Infection		P1	P2	P3	P4	P5	P6	P7	P8
Global	AIC	4563.709	4520.157	4358.771	5208.628	4880.418	3669.194	4585.068	4712.721
	Adj. R^2	0.302	0.475	0.514	0.269	0.377	0.654	0.461	0.426
GWR	AIC	2616.868	2957.69	2819.464	4313.632	2416.668	2628.307	3421.455	3045.657
	Adj. R^2	0.806	0.794	0.815	0.598	0.849	0.829	0.748	0.794
Mortality					P4	P5	P6	P7	P8
Global	AIC	—	—	—	5753.527	5656.292	5832.418	5856.458	5843.406
	Adj. R^2	—	—	—	0.048	0.092	0.012	0.001	0.006
GWR	AIC	—	—	—	3874.371	3805.427	5042.266	4946.023	4354.213
	Adj. R^2	—	—	—	0.679	0.694	0.418	0.471	0.574

weeks phase, with 1% decrease of mobility on public transit, the infection rates drop between 0.522 and 0.808 in those 2-weeks phases (between 522 and 808 per 100, 000 population). This spatial factor remaining significant for infection in all phases indicates that mobility-restricted public transit has a significant and consistent impact on infection.

In addition, the nativity of ethnic minority shows great differences between different nativities as well as phases. For example, coefficients for Asians (FB) and Asians (NB) are generally negative, indicating that census tracts with a higher share of Asian population tend to have lower infection rates. This is likely due to the fact that many Asians started wearing masks way earlier than the mask mandate (Wang, 2020). As the outbreak of COVID-19 was first reported in China, Asian Americans have started taking cautions such as wearing masks and sanitizing hands at the early stage when cases were reported in New York. However, there are a couple exceptions. For example, Asians (FB) are positive in Phase 5 and Asians (NB) are positive in Phase 8. While it might indicate a brief outbreak among Asian communities during these two phases, a more in-depth examination is needed to better understand the anomalies in these two phases and to further identify the specific Asian sub-group which was impacted, and the likelihood associated with working in essential business. In contrary, Hispanics (NB) generally contributes positively to infection rate with one exception of Phase 4 when Hispanics (FB) contributes positively to infection rate. This shows that census tracts with higher percentage of Hispanics (NB) generally have higher infection rates, and in Phase 4 census tracts with a large share of Hispanics (FB) have higher infection rates. Surprisingly,

Table 6. Coefficients of global regressions on infection rate in each phase.

Infection	P1	P2	P3	P4	P5	P6	P7	P8
Mobility-restricted transit	0.533**	0.69**	0.717**	0.522**	0.6**	0.808**	0.678**	0.644**
Blacks (NB)	0.007	−0.039	−0.032	−0.019	−0.018	0.037	−0.033	−0.01
Blacks (FB)	0.005	0.023	−0.03	0.021	0.098**	0.013	0.028	0.014
Asians (NB)	−0.009	−0.026	−0.014	−0.004	−0.064*	0.042	−0.007	0.078**
Asians (FB)	−0.069*	−0.017	−0.053	−0.055	0.071*	−0.018	−0.01	−0.066*
Hispanics (NB)	0.136**	0.072**	−0.008	−0.056*	0.162**	0.028	0.096**	0.12**
Hispanics (FB)	−0.04	−0.014	−0.021	0.047*	0.009	0.025	−0.001	−0.003
SVI: Socioeconomic status	−0.056	0.023	0.046*	0.079**	−0.022	0.028	−0.006	0.039
SVI: Household composition	0.009	0.021	−0.007	0.032	0.01	−0.024	−0.009	−0.013
SVI: Housing/ Transportation	−0.087**	−0.027	0.026	−0.006	0.055**	0.057**	0.044	0.051**

** $p < .05$.
* $p < .1$.

Table 7. Coefficients of factors to mortality rate in each phase.

Mortality	P4	P5	P6	P7	P8
Mobility-restricted transit	0.203**	0.088**	0.096**	0.033	0.058**
Blacks (NB)	0.013	0.226**	0.092**	−0.008	−0.02
Blacks (FB)	−0.012	0.068**	−0.068*	−0.025	0.021
Asians (NB)	−0.106**	0.005	0.069	−0.058	0.14**
Asians (FB)	0.127**	0.196**	−0.037	0.016	−0.083*
Hispanics (NB)	0.071**	0.013	0.02	−0.004	0.029
Hispanics (FB)	0.02	0.087**	−0.007	−0.027	0
SVI: Socioeconomic status	−0.08**	−0.176**	−0.037	0.033	−0.018
SVI: Household composition	0.054*	0.09**	0.055*	0.024	0.052*
SVI: Housing/Transportation	0.052**	−0.156**	0.005	0.028	−0.003

** $p < .05$.
* $p < .1$

neither Blacks (NB) or Blacks (FB) are significant except in Phase 5. In addition, vulnerability of socioeconomic status (Phase 3 and Phase 4) and housing type (Phase 5, 6, and 8) are positive in those specific phases. For vulnerability of socioeconomic status, it directly relates to resident's income level and financial insecurity, who may work in essential business and continue working during the pandemic. Related to the vulnerability of housing types, since a large portion of NYC population lives in multi-unit structures with shared entrances and crowding (Furman Center for Real EstateUrban Policy, 2010), which are likely contributing to the higher infection rates in those census tracts.

Results from global regressions for mortality rates are shown in Table 7. This factor of mobility-restricted transit also remains as a significant factor to mortality rate in all phases except in Phase 7. With 1% decrease in mobility-restricted transit, the mortality rates drop between 0.058 and 0.203 in

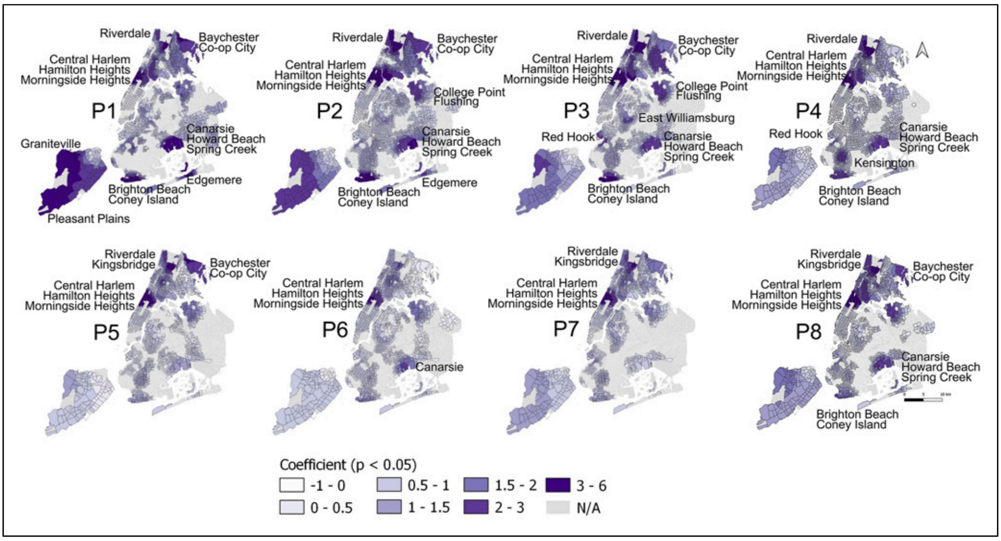

Figure 3. Significant coefficients of mobility-restricted transit in GWR on infection rates.

2-weeks phases. In addition to the spatial factor, the nativity of minority is showing more contrasting impacts between groups and phases. For example, census tracts with more population of Blacks (both NB and FB) have higher mortality rates with the only exception that Blacks (FB)' effect is negative in Phase 6. Hispanics (NB) contribute positively to mortality rates in Phase 4 while Hispanics (FB) contribute positively in Phase5. However, the nativity of Asians shows contrasting effects in the same phase and changing effect over time. In Phase 4, Asians (FB) are contributing positively to the mortality rates, but Asians (NB) are contributing negatively. In Phase 5, Asians (FB) are also contributing positively to mortality rate. But in Phase 8 this contrast is opposite that Asians (FB) are contributing negatively but Asians (NB) are contributing positively to mortality rate. These contrasting and dynamic effects of Asian nativity are very interesting; yet without information of healthcare access and individual behavior, it is hard to pinpoint reasons for this pattern. Out of all social vulnerability categories, household composition has a strong positive effect across phases. As higher percentage of population with age 65 or older contributes to higher vulnerability in this category, it is likely that census tracks with a larger share of senior citizens have higher mortality rates (Gold et al., 2020). Socioeconomic status is negative in Phase 4 and 5, while housing/transportation is positive in Phase 4 but negative in Phase 5, and neither is significant in later phases. Further in-depth analysis is needed to better understand this, and other factors such as pre-existing health condition and access to health care should be considered in follow-up research.

Geographically weighted regression (GWR)

Different from global regression which does not consider the proximity to locations, GWR considers the proximity to locations (census tract in this study) are not even across space, hence a factor in the local regression. As shown in Table 4, the GWRs result in much higher coefficients of determination which explains about 80% of deviance in both infection and mortality rates.

As mobility-restricted transit remains a significant factor in global regression, GWRs further identify the census tracts where mobility-restricted transit is a significant factor in all phases, which are mapped in Figure 3. The patterns shift over time. The hotspots of very high impact of mobility-restricted transit on infection exist in every borough at the beginning. In the first two phases,

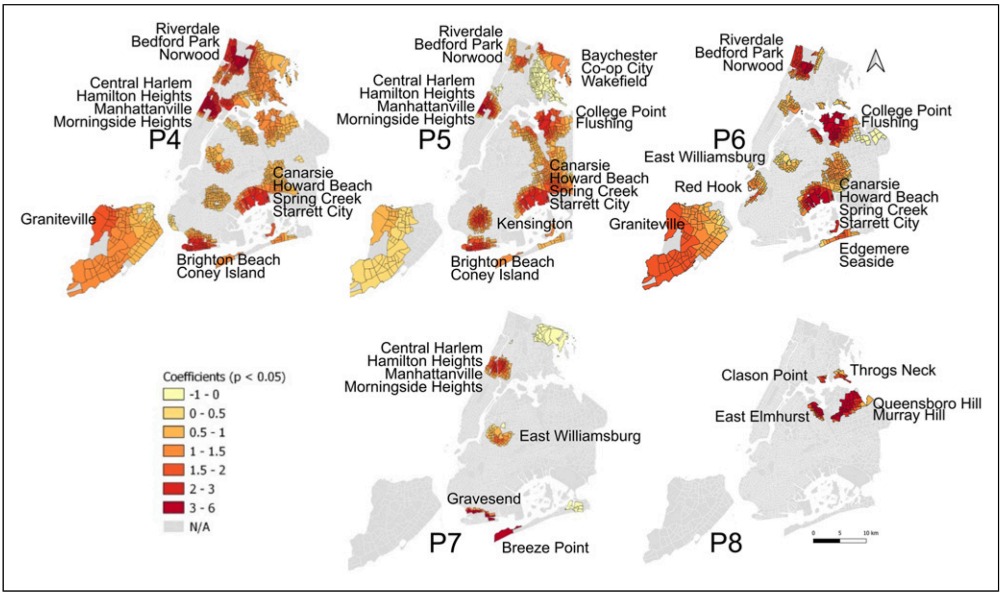

Figure 4. Significant coefficients of mobility-restricted transit in GWR of mortality rates.

neighborhoods where mobility-restricted transit with very high coefficients include Central Harlem, Morningside Heights, Washington Heights and Hamilton Heights in Manhattan, Riverdale and Baychester in Bronx, Brighten Beach in Brooklyn, Canarsie, Spring Creek, Howard Beach, Edgemere, College Point, Flushing in Queens, and large parts of Staten Island including Graniteville and Pleasant Plains. Many neighborhoods on Staten Island do not show transit as a significant factor due to lower mobility starting from Phase 3. A new hotspot including the neighborhoods around Kensington in Brooklyn appears since Phase 4.

A large percentage of these neighborhoods are dominated by minorities. For example, neighborhoods around Central Harlem have large population of Blacks (NB), but neighborhoods around Washington Heights have large population of Hispanics (FB), mostly from the Caribbean. In particular, the census tract No. 245.00 of Manhattan borough in Washington Heights neighborhood has the largest concentration of Dominican immigrants (Fessenden and Roberts, 2011). It is also important to point out that Brighten Beach and Coney Island neighborhoods in southern Brooklyn show a high impact of mobility in public transit on infection. These neighborhoods are largely dominated by non-Hispanic White immigrants from Eastern Europe. In particular, the census tract No. 360.02 has the largest concentration of immigrants mainly from Ukraine, Russia, and Uzbekistan (Fessenden and Roberts, 2011). This confirms that minority is not only simply based on race but also based on ethnic and cultural origins, and consideration of additional minority group such as these non-Hispanic White (FB) population is also necessary in future studies.

The GWRs of mortality rate in each phase reveal more varying temporal patterns across phases. Figure 4 shows the census tracts where the factor of mobility-restricted transit is significant in GWRs. A few local clusters can be identified. In Phase 4, 5, and 6, clusters exist in every borough. Neighborhoods including Central Harlem, Washington Heights, Morningside Heights and Manhattanville in Harlem, Riverdale, Bedford Park, Norwood, Wakefield, and Co-op City in Bronx, East Williamsburg, Ditmas Park, Coney Island, and Brighton Beach in Brooklyn, College Point, Downtown Flushing, Spring Creek, Howard Beach, Seaside, and Starrett City in Queens, and Graniteville and Howland Hook on Staten Island. Only in Phase 5, new cluster in Brooklyn appears,

Figure 5. Significant coefficients of minority population nativity in GWR of mortality rate in Phase 5.

which are neighborhoods surrounded by Kensington, Borough Park, Midwood, and Ocean Parkway in Brooklyn. These are neighborhoods with large Jewish communities. There were large gatherings reported in news then which may have contributed to high infection and mortality in these phases (Stelloh, 2020). Since Phase 7, there are no longer clusters on Staten Island but in the other four boroughs. The number of clusters reduced except Harlem neighborhoods in Manhattan, Baychester in Bronx, East Williamsburg and Gravesend in Brooklyn, and Breeze Point in Queens. The clusters further reduced in Phase 8 except Clason Point, and Throgs Neck in Bronx and East Elmhurst, Queensboro Hill, and Murray Hill in Queens.

In addition to the spatial factor, the patterns resulted from nativity are also noticeable, further confirming the significant disparities among minority communities. The patterns show neighborhoods with specific nativity of minority population contributing either positively or negatively to mortality rates at different times. Figure 5 shows the various patterns of each individual nativity factor to mortality rate in Phase 5. Blacks (NB) in Riverdale in Bronx, Forest Hill and South Jamaica in Queens are contributing positively to mortality rates. But Blacks (NB) population in Flushing, Flatbush, and Fresh Meadows are showing negative impacts. It is very likely that the share of Black population in these census tracts are very low. For example, Fresh Meadows is a neighborhood resided mostly by immigrants from East Asia such as Korea (Fessenden and Roberts, 2011). Other neighborhoods also have higher percentage of population in other ethnic groups. Baychester is the neighborhood where Blacks (FB), Asians (FB), and Hispanics (FB) positively contribute to mortality rates. In addition, Blacks (FB) residing in College Point in Queens, Asians (FB) in Harlem, Springfield Gardens and Far Rockway in Queens positively contribute to mortality rates. These complex results show not only significant disparities between different minority groups but also between nativities within the same minority group. It is very likely that different nativities of Hispanics and Asians do not have the same concentration in a particular neighborhood. But Blacks with different nativities seems to have a mixed concentration in the same neighborhoods. A more in-depth investigation within those neighborhoods in terms of the composition of specific communities is needed to understand their health disparities better and provide essential evidence to suggest localized support.

Discussion and Conclusions

This research contributes to the emerging literature in minority health disparities by adopting a spatial and a temporal perspective and by taking a case of NYC. Results demonstrate the significant and complex impacts of spatial, racial and social factors, which shape the disparities of COVID-19 outcomes among neighborhoods. At the city level, the spatial factor of mobility-restricted transit shows significant impact on COVID-19 infection and mortality within each 2-weeks period. Using aggregated movement data tracked by mobile phones, this study derives the time people not staying at home during the lockdown period as a weight to approximate the restricted mobility during pandemic. As the lockdown policy is partial which still allows people to shop in grocery stores or do other essential business, it is inevitable that workers in essential business still rely on public transit. Results show that using public transit can significantly increase the risk of being infected and dying, especially at time when mask mandate is not even introduced.

Communities in which high infection or mortality exist show a large demand for public transit. Majority of these communities are where minority population reside, which can be linked to the population of essential workers. On one hand, traditionally Hispanic or Blacks neighborhoods are highly impacted. Neighborhoods such as Central Harlem, Morningside Heights, Washington Heights and Hamilton Heights in Manhattan, Baychester in Bronx, College Point, Howard Beach, and Canarsie in Queens are large communities with dominant Black or Hispanic population. In particular, Central Harlem and Howard Beach are the hotspots of COVID-19–related mortality for a few phases. On the other hand, some non-Hispanic White neighborhoods including Brighton Beach in Brooklyn, and Graniteville and Bloomfield on Staten Island also have high infection due to mobility-restricted transit. Brighton Beach neighborhood, in particular, has a very large population of immigrants from Eastern Europe including Russia and Uzbekistan while neighborhoods on Staten Island have a large percentage of Italian descendants. The results suggest that population residing in these communities might have similar socioeconomic status and professions as ethnic minorities. Commuting to work on public transit can expose them to a higher risk of contracting the virus. While the social vulnerability is associated with minority population, the pandemic outcome is not simply based on race or ethnicity but also the working, living, and health conditions as indicated by SVIs. Future research addressing these neighborhoods with additional minority factors is further needed.

In addition to the significant spatial factor, this study reveals that the nativity of ethnic minorities leads to different pandemic outcomes, whose patterns change across space and time. In this study period, Asians (FB) and Hispanics (NB) are prone to high mortality when Asians (NB) and Hispanics (FB) are not, or vice versa. When Blacks are significantly associated with mortality, both FB and NB Blacks show a similar pattern at first. This may imply different residing patterns of minority population. For blacks, both FB and NB population may concentrate in the same communities. But for Hispanic and Asians, their residing communities may vary between FB and NB population. For example, a community with large concentration of Asians (FB) may have very low concentration of Asians (NB). In addition to the findings of nativity associated with COVID-19 mortality at the ZIP code level (Friedman and Lee, 2021), this study provided additional evidence on the different residential concentrations of minority nativity, which lead to different spatial and temporal pattern over space and time. These complex and dynamic findings demonstrate that not only differences are between different minority groups, but also differences are between different nativities within the specific minority group. These hotspots identified in the results show the need of further investigation of underlying causes in those communities and suggest community-specific support.

A few limitations exist in this study. First, it is important to point out that the mobility-restriction transit is an estimate of the actual ridership. Due to the lack of individual bus ridership, this study uses the number of stops and population in each census tract to simulate the potential ridership. Second, this study uses the calculated average percentage of time not spending at home as the weight to imitate the mobility, which may not all be in public transit. Therefore, it is necessary to derive more accurate measure of ridership using public transit. Methods such as space syntax has been used for investigating the transmission of virus in buildings (Dietz et al., 2020), which can be developed for understanding the association between public transit and the transmission of COVID-19. Third, the used SVI seems too general to model pandemic outcomes. Additional socioeconomic factors such as occupational structure, poverty, education level, and health condition should be considered in future studies. Fourth, this study does not consider foreign-born Whites who may also be working in essential business. Therefore, introducing factors to cover a larger scope of minority groups, such as foreign-born non-Hispanic Whites, may add more clarity to the understanding of their association with infection and mortality. Besides nativity, a closer look at specific factors such as the occupational structure, poverty, education level, and health condition may also help identify the underlying causes to the disparities among neighborhoods that are further impaired by this pandemic.

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