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The lockdown, mobility, and spatial health disparities in COVID-19 pandemic: A case study of New York City

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ABSTRACT

The world has adopted unprecedented lockdown as the key method to mitigate COVID-19; yet its effect on pandemic outcomes and health disparities remains largely unknown. Adopting a multilevel conceptual framework, this research investigates how city-level lockdown policy and public transit system shape mobility and thus intra-city health disparities, using New York City as a case study. With a spatial method and multiple sources of data, this research demonstrates the uneven impact of the lockdown policy and public transit system in shaping local pandemic outcomes. Census tracts with people spending more time at home have lower infection and death rates, while those with a higher density of transit stations have higher infection and death rates. Residential profile matters and census tracts with a higher concentration of disadvantaged population, such as Blacks, Hispanics, poor and elderly people, and people with no health insurance, have higher infection and death rates. Spatial analyses identify clusters where the lockdown policy was not effective and census tracts that share similar pandemic characteristics. Through the lens of mobility, this research advances knowledge of health disparities by focusing on institutional causes for health disparities and the role of the government through intervention policy and public transit system.

1. Introduction

With a novel coronavirus (COVID-19) and before vaccine was available to the public recently, much of the world has adopted the lockdown in various forms as the key measure to control this pandemic; yet, its effect on pandemic outcomes remains largely unknown. From the draconian sealing-off in Wuhan, China, to a nationwide lockdown in Italy, and to piecemeal stay-at-home orders in the U.S., the lockdown has transformed the world beyond recognition. While it has been adopted as one of the key responses to pandemic threats in history (e.g. Bajardi et al., 2011; Charu et al., 2017; Peiris & Guan, 2004; Pyle, 1969; Yang & Taylor, 2016), mobility restrictions adopted 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 health disparities. In addition to vast national and regional differences due to different onsets of the pandemic, different government interventions and public health infrastructure (e.g. Ren, 2020; Gargoum & Gargoum, 2021; Noland, 2021), there are tremendous health disparities within the city despite the same lockdown policy, with poor neighborhoods and disadvantaged groups such as ethnic minorities suffering disproportionately high rates of infection and death (CDC, 2020a, 2020b, 2020c; Chen, Waterman, Krieger, & Krieger, 2020; Thebault et al., 2020; Yancy, 2020). Thus, the lockdown policy has exhibited multilevel and multi-dimensional effects on pandemic outcomes, and there is a critical need to assess its differentiated impact in order to adequately address health disparities.

Since the Chinese city of Wuhan, the first epicenter, adopted a draconian lockdown policy on Jan. 23, 2020, different nations and regions have adopted various lockdown policies to contain the pandemic but with varying outcomes. First, the lockdown policy has been adopted at different timings with different degrees of mobility control across nations. After the initial denial and delay, China adopted a strict lockdown policy in Wuhan and other Chinese cities, which halted virtually all mobilities but has significantly reduced the number of infections (e.g. Fang, Wang, & Yang, 2020; Qiu, Chen, & Shi, 2020). Elsewhere, countries that adopted the lockdown policy early in the pandemic such as Germany, New Zealand, Canada, and Norway have lower death rates while maintaining relatively higher mobility than those with delayed lockdown such as Spain, France, Italy, the U.K., and the U.S. (Gargoum & Gargoum, 2021). Different political systems and political dynamics...
have resulted in rather different implementations of the lockdown. Comparing China, Italy and the U.S., Ren (2020) argues that the central-local government relations and the strength of local territorial institutions shape the implementation of lockdown polices. China adopted a top-down approach and utilized a network of local institutions at the neighborhood level to enforce the lockdown policy, which have been more effective than the piecemeal, localized rollout of the lockdown, the lack of central-local coordination, and the lack of local institutions for enforcement in Italy and especially in the U.S. The public compliance with the lockdown policy also varied significantly across nations. Despite its draconian measures, China has experienced little resistance from the public, while many nations, both rich and poor, witnessed massive anti-lockdown protests (Carothers & Press, 2020; Meeker, 2020). Yet, it is probably fair to say that the lockdown (and mask wearing) has been the most politicized and the least successful in the U.S., which has significantly hampered its effort to restrict mobility and mitigate the pandemic. In addition, prior experience of SARS pandemic in 2003 and subsequent upgrade in public health infrastructure have also helped some Asian countries/regions launch timely and vigorous responses to mitigate COVID19 pandemic (e.g. Lee, Chiew, & Khong, 2020; Summers et al., 2020).

Secondly, the lockdown policy has been implemented differently at the local level. Even in authoritarian China, cities adopted their own versions of lockdown policy with different degrees of mobility reduction and business shutdown (Ren, 2020). Some Chinese cities adopted a strict lockdown to avoid possible outbreak while others such as Shanghai were more confident in their abilities in containing the pandemic thus adopted a more lenient lockdown. With the dysfunctional federalism and the lack of leadership role from the Trump administration, local governments in the U.S. are left to make their own responses, with vastly different lockdown policies across cities and states. San Francisco was the first city in the nation to adopt a stay-at-home order on March 17, 2020, followed by other major cities (e.g. March 22 in NYC and March 21 in Chicago) and states, while seven states such Iowa, Nebraska, North Dakota, South Dakota, Utah, and Wyoming did not issue such orders in March and April of 2020. The lockdown in the U.S. is also loosely implemented, encouraging citizens to stay at home (but with no way to enforce it), shutting down only non-essential businesses while keeping public transit running and the road system open. Despite significant reduction, mobility remained relatively high in the U.S. as people continued to run errands, go to work, and exercise outdoor. In other words, the lockdown in the U.S. relied heavily on individual efforts and a certain segment of the population has resisted the lockdown. As a result, the impact on mobility reduction is less effective and pandemic outcomes vary significantly across locales (Glaeser, Gorback, & Redding, 2020). Similarly, despite the nationwide lockdown and using the police to enforce the lockdown, different municipalities in Italy implemented the policy with different degrees of mobility restrictions, depending on their fiscal capacity and income level (Bonaccorsi et al., 2020).

Existing research on government intervention has focused on different pandemic outcomes between nations, regions, or cities resulted from different lockdown policies. The underlying assumption is that the lockdown policy is usually uniform within the city, and thus its impact would be similar across neighborhoods and social strata. However, this is clearly not the case. In London, Chicago, and New York, minorities and low-income groups from disadvantaged neighborhoods are less likely to reduce mobility during both work and non-work hours than those in more affluent neighborhoods; thus experience higher risks of infection (TruMP and Cheshire, 2021; Chang, Pierson, Koh, et al., 2021; Coven & Gupta, 2020). This difference in mobility reduction is probably a result of existing socioeconomic inequalities as different social strata respond to lockdown differently. For example, while professional high-income earners can work from home under the lockdown, the poor often have no access to high-speed internet due to the digital divide or their jobs such as sales and services usually cannot be performed from home (Tanguay & Lachapelle, 2020; Valentino-DeVries, Lu, & Dance, 2020). Transportation inequality is another reason for different mobility reductions, as the poor rely on public transit for daily activities even during the pandemic, which has been argued by some as the main reason for racial disparities in pandemic outcomes (McLaren, 2021). The elderly population is another group that is disproportionately affected by the lockdown, with cuts to public services, the loss of social infrastructure and pressures on the voluntary sector during the lockdown (Buffel et al., 2021).

The rapidly growing body of literature has helped us better understand the COVID-19 pandemic. Social scientists have reaffirmed human mobility as a main reason for virus transmission and the importance of government intervention on pandemic outcomes (e.g. Elliott, 2020; Musselwhite, Avinerti, & Susilo, 2020). However, existing research has mainly studied infections and deaths in different cities/counties and countries, while well documented disparities within the city have been under-studied probably due to the lack of data. More importantly, while mobility restriction is widely implemented in this pandemic, it remains unclear how it shapes pandemic outcomes as existing studies show rather mixed findings (e.g. Chinazzi et al., 2020; Lai et al., 2020; Summers et al., 2020).

This paper focuses on intra-city health disparities and aims to determine how the government intervention and the transit infrastructure shape mobility and thus health disparities in COVID19 pandemic. The central hypothesis is that the same lockdown policy and public transit system in the city have uneven impact across neighborhoods and contribute to spatial health disparities in this pandemic. This research expands the literature on social determinants of health (SDOH) to infectious diseases and highlight institutional forces in shaping mobility patterns and thus exposure and infection risks. It advances knowledge of health disparities by examining the roles of government intervention and the public infrastructure on top of socioeconomic indicators. This research also contributes to the literature on mobility and the infrastructure turn in urban scholarship.

After reviewing the literature, we layout a conceptual framework, emphasizing the uniqueness of infectious diseases and the role of mobility, to understand pandemic outcomes and health disparities. Hypotheses will be tested through an empirical analysis of New York City using multiple sources of data, followed by conclusions and discussion.

2. Literature review, conceptual framework and hypotheses

There has been a rapidly growing body of literature devoted to the understanding of pandemic outcomes, and its impact on people and the society. The following review focuses on health disparities, and associated factors including mobility, transport network, and government policies.

2.1. Health disparities and social determinants of health

The COVID-19 pandemic has exhibited significant health disparities. In addition to vast national and regional disparities due to different onset of the pandemic, different interventions, and public health infrastructure (e.g. Ren, 2020; Gargoum & Gargoum, 2021; Noland, 2021), 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 are prone to more severe illness, even fatalities (Bonow, Fonarow, O’Gara, & Yancy, 2020; Gressel, Zangrillo, Zannella, et al., 2020; Shi, Qin, Shen, et al., 2020). In the U.S., ethnic minorities suffer the most from the pandemic. Blacks are 1.4 times more likely to be infected, 3.7 times more likely to be hospitalized and, 2.8 times more likely to die than non-Hispanic Whites, and the corresponding ratios for Hispanics are 1.7, 4.1 and 2.8, respectively (CDC, 2020b). Making up only 13% of the total population, African Americans accounted for 23% of deaths from COVID-19 (APM Research...
This striking racial disparity persists even after adjusting for comorbidities, age, sex, and income (Azar et al., 2020; Yancey, 2020), which calls for scrutiny of its underlying forces beyond conventional sociodemographic factors.

Social determinants of health (SDOH) are conditions in the environments where people live, learn, work, and play that affect a wide range of health risks and outcomes (CDC, 2020c). SDOH includes five key areas, including healthcare access and quality, education access and quality, economic stability, neighborhood and built environment, and social and community context. SDOH has been widely adopted to explain health disparities in general (e.g., Marmot and Wilkinson, 2005; WHO, 2008) and in the COVID-19 pandemic (Moore et al., 2020; Wilkins, Friedman, Churchwell, et al., 2021). SDOH can influence exposure, susceptibility, testing, and treatment of COVID-19 and consequent pandemic outcomes. For example, residents in marginalized neighborhoods are at risk for higher exposure rates due to factors such as residential crowding, inability to work from home, and necessary use of public transportation (Singu, Acharya, Challagundla, & Byrareddy, 2020; Wilkins et al., 2021). Susceptibility to COVID-19 and risk of more severe outcomes are related to not only pre-existing conditions and their disparities (Moore et al., 2020) but also the stress from daily life and discrimination, the latter of which may lead to physiological changes that increase susceptibility including dysregulation and inflammation (Wilkins et al., 2021). Systemic inequalities in access to healthcare not only shape pre-conditions among marginalized populations, but also constrain their access to testing and treatment for COVID-19, which leads to their higher rate of infection and death. For example, in the U.S., counties with Medicaid expansion have a lower COVID-19 incidence rate (Liao and De Maio, 2021). Finally, changes in healthcare technology may have contributed to inequalities in COVID-19 testing and treatment and exacerbated health disparities (Leslie et al., 2021; Wilkins et al., 2021).

2.2. Transport network and mobility

Transport network and human mobility have long been considered important factors in disease transmission, from waterway/road systems in a cholera outbreak in the 19th century to subway system and air travel in recent epidemics such as SARS (e.g., Goscé & Johansson, 2018; Peiris & Guan, 2004; Pyle, 1969; Rvachev & Longini, 1985). For COVID-19 pandemic, scholars have confirmed the importance of transport network and mobility. Mussewhite et al. (2020) attribute the rapid spread of COVID19 virus to the hypermobility of our current lifestyle with international and domestic transport networks and globalization. Wuhan is a transportation hub in China with extensive air and train systems, and the virus has already transmitted to other Chinese cities and countries in January 2020 before its lockdown (Wu and Zhang, 2021). Wilson and Chen (2020) noted the virus spreads most quickly and proportionally to the cities with the greatest passenger volume from Wuhan International Airport, and Zheng, Xu, Wang, Ning, and Bi (2020) find a significant and positive association between the frequency of flights, trains, and buses from Wuhan and the daily and cumulative numbers of COVID-19 cases in other cities with progressively increased correlations for trains and buses. Mobility is especially related to the initial infection rate, according to the conventional Susceptible-Infected-Recovered (SIR) model (Rerrack & McKendrick, 1927). In particular, public transportation system potentially can impose high risk for the COVID19 contagion, as 1) people are confined in limited space, 2) there might be scarce access control to identify sick passengers, and 3) there are multiple surfaces such as seats, doors, handrails and ticket machines that can easily transfer germs (UITP, 2020). Harris (2020) argues that the subway system in New York City (NYC) is a major disseminator of coronavirus virus at least during the initial spread of this epidemic. Kavvila and Sakamoto (2020) also argue that mobility networks, together with other critical infrastructure such as healthcare facilities, food and nutrition, and open space, contribute to COVID19 risk at the zip code level in NYC. Using data for 3140 counties in the U.S., McLaren (2021) find racial disparity for African Americans and First Nations population can be sourced mainly to the use of public transit, instead of differences in income, poverty rate, education, occupational mix or even access to healthcare insurance.

During the pandemic, urban travel declined significantly but unevenly across transport mode and between cities and neighborhoods. In general, there is a significant shift away from public transport to cars, bikes/motorcycles, and walking due to the perception of high risks associated with public transportation and reduced service supply (Molloy et al., 2020; Tirachini & Cats, 2020; Zhang, Hayashi, & Frank, 2021). However, access to different transport modes varies between social groups, and transport inequality has been well documented. Low-income population often do not own private cars in auto-oriented societies such as U.S. and U.K., and they have to rely on public transport for work and other daily activities, which tends to exacerbate their socioeconomic disadvantages and exclusion (e.g. Banister, 2018; Clifton & Lucas, 2004; Li, Dodson, & Sipe, 2015). During the COVID 19 pandemic, high-income population is more likely to work from home and avoid public transport, while low-income residents have no option but to continue to use public transport, which may lead to different exposure risks and pandemic outcomes. In addition, the poor and minority population bear the brunt of the coronavirus-spurred economic crisis. The unemployment rate in April 2020 was 16.7% for Blacks, 18.9% for Hispanics, much higher than 14.2% for Whites in the U.S. (Bureau of Labor Statistics (BLS) & US Department of Labor, 2020), and half of lower-income Americans have reported losing their job or have experienced a significant loss in wages (Parker et al., 2020). This economic hardship disadvantaged population experiences during the pandemic may force them to use affordable public transit, which further increases their infection risk and potentially exacerbates their pandemic outcomes (McLaren, 2021).

2.3. 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; Charu et al., 2017; Wang & Taylor, 2016). However, the lockdown during the COVID-19 pandemic is unprecedented, with its scale, magnitude and duration as many regions and countries adopted. Yet, empirical findings on its effect are mixed. Some scholars find that the lockdown has been very effective in lowering infections and controlling the spread of COVID-19 despite its devastating economic and social impacts (Bonaccorsi et al., 2020; Elliott, 2020; Musselwhite et al., 2020). Research on China shows 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 factors such as population size, wealth, and distance from the risk source (Jia et al., 2020; Fang et al., 2020). The strict lockdown policy in Wuhan and the rest of China has significantly reduced the total number of infections (Fang et al., 2020; Qiu et al., 2020). Despite more lenient and localized lockdown policy in the U.S., Glaeser et al. (2020) studied five major cities and find on average about 20% decrease in the number of COVID-19 cases per capita for every 10% decrease in mobility between February and May 2020. However, others criticize the effectiveness of the lockdown policy in containing COVID-19. For example, both Chinazzi et al. (2020) and Lai et al. (2020) find that travel bans, while effective, are not as effective as other non-pharmaceutical interventions such as early detection, hand washing, self-isolation, and household quarantine. The relative successful mitigation of the pandemic in Taiwan without a lockdown indicates the effectiveness of other measures such as early screening, quarantine, and mask use (Summers et al., 2020).

The lockdown policy has been implemented unevenly across space with different impacts on COVID-19 outcomes. The timing and the degree of the lockdown are important. Based on a time series analysis of
inequality and health inequality has long been established (e.g., Olden, in turn increases their health risks. This coupling between economic work from home, which forces them to commute to work in person and operators and elementary occupations have little to no opportunity to contrast, low-income people and those in sales and services, manual access to high-speed internet connection is highly correlated with in capita income as well as those with high fiscal capacities, which impact in municipalities with higher income inequality and lower per across cities, they find a 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).

Furthermore, the same lockdown policy can have different impact on subpopulations and neighborhoods within the city. Using cellphone data in Chicago, Chang et al. (2021) find that while the overall mobility dropped sharply in March after stay-at-home order was implemented, disadvantaged groups from low-income neighborhoods have not been able to reduce mobility as sharply in the first a few weeks of March 2020, and they had higher mobility than higher-income neighborhoods for most of March through May with more visits to crowded places such as grocery stores, thus experience higher infections. Coven and Gupta (2020) also argue that disparities in mobility response contribute to much of the observed disparities in infection and mortality in NYC, as residents in richer neighborhoods are substantially more likely to flee the city during the pandemic, while those in low-income, minority neighborhoods exhibit high intra-city mobility during both work and non-work hours. In addition, working from home has been shown to be a privilege of high-income earners (Tanguay & Lachapelle, 2020; Valentin-DeVries et al., 2020). On the one hand, there is a digital divide, as access to high-speed internet connection is highly correlated with income, thus the possibility to work from home increases with income (Chiou & Tucker, 2020). On the other hand, not all work can be performed at home. Only about one third of occupations in Italy and the U. S. can be performed at home, which are concentrated among high-paying managerial jobs, academics, technical professionals and clerical support work (Cetrule et al., 2020; Dingel & Neiman, 2020). In contrast, low-income people and those in sales and services, manual operators, elementary, and personal service occupations are often required to work from home, which forces them to commute to work in person and in turn increases their health risks. This coupling between economic inequality and health inequality has long been established (e.g., Olden, 2021), which only becomes more acute during the pandemic.

Existing studies demonstrate the complex impact of government intervention and transport system on pandemic outcomes, which calls for more research. While helping us understand COVID19 pandemic, existing studies have three limitations. First, there are many studies on health disparities and the lockdown policy, respectively; yet, few study the role of government policies in shaping health disparities. While the lockdown policy is implemented uniformly within the city, it tends to have differentiated effects on people and places due to existing economic and social inequality, thus lead to different pandemic outcomes. Second, most research on mobility uses population movement, such as the number of travelers and trips between cities and countries, to predict pandemic outcomes. There is little attention to the actual transport networks, whose physical configuration determines how people move within and between cities, and thus shapes disease transmission (Dietz et al., 2020). In particular, the public transit system offers small indoor space and brings people from and to different parts of the city, which offers pathways for disease transmission. It is also part of the critical infrastructure in cities that shape urban health vulnerability (Kawira & Sakamoto, 2021), and inequalities in transport, economy, and health. Thus, the role of public transit system in health disparities deserves scrutiny. Finally, while existing data show significant spatial inequality in infections and deaths, few studies adopt spatial methods to study this pandemic. Infectious disease is fundamentally a spatial phenomenon with a virus transmitted through human contact. Some recent studies used the spatial method, such as Lyanda, Boakye, Lu, and Oppong (2021) on rural-urban disparity in case fatality ratio in the U.S., Wu and Zhang (2021) on COVID19 cases in Texas, Mollalo, Vahedi, and Rivera (2020) on incidence rate in the U.S., and Al Kindi et al. (2021) on Oman. However, these studies are at the national, state, or county level, with few research at the neighborhood level. Intra-city disparities in pandemic outcomes have been well recognized; yet in-depth analyses have been limited, probably due to the limitation of available data at a small spatial scale. Even in the U.S. where open access to data is emphasized, few cities have released pandemic data at sub-city level.

Based on existing literature and given the nature of infectious diseases, we propose a multilevel conceptual framework that is centered around human mobility within the general framework of social determinants of health (SDOH) to understand health disparities in pandemic outcomes. SDOH is a place-based framework incorporating various social, economic, and environmental conditions that affect health risks and outcomes (CDC, 2020C; Singu et al., 2020). However, SDOH gives little consideration to the uniqueness of infectious diseases, where human mobility and potential contact/exposure are essential to health outcomes. We believe that pandemic outcomes are shaped by individual/household social economic status (SES), neighborhood SES, and the government through intervention policies and public infrastructure at the city level (Fig. 1). First of all, individual/household SES directly affects health outcomes in a pandemic. In addition to factors such as age, race, underlying diseases, and income that have shown to be important to health (e.g. Bonow et al., 2020; Grasselli et al., 2020; Shi et al., 2020), we highlight the roles of occupation/education, commuting mode, and housing in pandemic outcomes. As discussed earlier, working from home is a privilege for mostly the educated and high-income earners, and about two thirds of occupations have to be performed in person with human contact, which increases risks of virus exposure and infection. Similarly, people who rely on public transit have higher risks than those who drive or can stay-at-home. Meanwhile, housing conditions, such as tenure (owning vs. renting) and crowding, can significantly affect the risk of infection and prevent the needed quarantine and social distancing when a household member is infected with COVID19.

Secondly, neighborhood SES can determine both individual and neighborhood health outcomes during a pandemic. As we discussed earlier, there is a large body of literature on SDOH for general health (e. g., Marmot and Wilkinson, 2005; WHO, 2008 Singu et al., 2020); yet, research on infectious diseases and COVID19 pandemic is still very limited. While we acknowledge the importance of many neighborhood factors, we highlight the roles of neighborhood crowding and ethnic composition in pandemic outcomes. Residents in crowded neighborhoods and ethnically marginalized neighborhoods often have higher
risks of infection due to factors such as difficulty to practice social distancing, the need to use public transit and work in person, and systematic barriers in access to testing and treatment for COVID19.

Thirdly, at the city level, the government can significantly shape pandemic outcomes and intra-city health inequalities through policy interventions such as the lockdown policy and physical infrastructure such as public transit and health care system. As discussed earlier, when and how the city government implement the lockdown policy directly determine the degree and patterns of human mobility in the city, thus affect infection and death. Meanwhile, the public transit system shapes mobility patterns through its physical setup and reduced services under the lockdown policy. Cities may also be connected to the rest of the world through regional and international transport system, which is especially important at the beginning of the pandemic (e.g. Musselwhite et al., 2020; Wilson & Chen, 2020; Wu & Zhang, 2021; Zheng et al., 2020). However, cities become a closed system after the lockdown policy is implemented and travel bans are in place, and local public transit system becomes the dominate force in enabling mobility. In addition, the quality, capacity, and accessibility of the health care system are essential to the overall pandemic outcomes. Under the restricted mobility during a pandemic, access to health care including testing and treatment for infections can be different within the city, resulting in health disparities in pandemics.

Finally, individual/household, neighborhood SES, and city level factors mediate each other in shaping pandemic outcomes. Individuals/households and neighborhoods with different SES respond differently to changes due to the pandemic and subsequent mobility restrictions and thus are affected differently by the city level policy. For example, during the lockdown, individuals and neighborhoods with lower SES are less likely to stay at home and reduce mobility than those with higher SES, thus experience higher infections (e.g. Chang et al., 2021; Coven & Gupta, 2020). During the pandemic, unemployment rises, social support structure changes, and transportation especially public transit changes, all resulting in different mobility patterns between social groups and between neighborhoods, including untenable travel to clinics/locations for testing and treatment of COVID19. These interactions between city level factors and individual and neighborhood SES, along with direct relationships between individual and neighborhood SES and health outcomes, increase the COVID-19 infection and case fatality among vulnerable groups and in disadvantaged neighborhoods. In other words, pandemic outcomes and health disparities are affected directly by factors at individual/household, neighborhood, and city level factors as well as mediations among them.

With the lack of individual level data, this research aims to determine how city-level and neighborhood level factors shape the spatial outcomes and health disparities in a pandemic in major metropolitan areas in the U.S. The central hypothesis is that municipal governments, through both the lockdown policy and public transit networks, together with SDOH, contribute to spatial disparities in infection and death rates in American cities. While the lockdown policy reduces and the public transit system enables human mobility, their effects vary across neighborhoods, and contribute to disparities in infection and death rates.

This research contributes to the literature mainly in three ways. First and theoretically, this research advances knowledge of health disparities in infectious diseases by identifying institutional sources of health disparities and determine how the government, through policy interventions and the transport infrastructure, contribute to health disparities in COVID19 pandemic in the U.S. It expands research on SDOH from general health to infectious diseases, by focusing on factors shaping human mobility and thus exposure and infection risks. Secondly and methodologically, this research adopts a spatial approach to study intra-city pandemic outcomes, an intrinsic spatial phenomenon. Non-spatial regressions have been conventionally used to predict health outcomes. However, infectious diseases tend to be clustered spatially and diffuse across space, and many underlying factors have spatially varying effects. Geographic theories are considered key in fighting this outbreak (Shepherd, 2020); yet existing studies using spatial approach focus on the city/county/state level with few at the sub-city level. This research studies intra-city health disparities at the census tract level and uses Geographically Weighted Regressions (GWR) to assess the spatially varying effects of public transit networks, and the lockdown policy. Thirdly, this research has significant policy implications to reduce...
health disparities and prevent and mitigate future public health crisis. For example, findings can reveal differentiated effectiveness of government interventions across neighborhoods and help to identify high-risk neighborhoods for location specific policy interventions during a pandemic. Findings on public transit can also inform future transport planning and policy to promote health equity.

3. Data and methods

New York City (five boroughs, hereafter NYC), the first epicenter in the U.S., is chosen for a case study. Availability of detailed pandemic data is the main reason to choose NYC. Despite the call for open data, most cities only release aggregated pandemic data at city or county level. NYC is one of the few cities that release data for zip code zones, which allows us to study intra-city health disparities. In addition to serving as a transportation hub, NYC has an expansive transit system with very high mobility and ridership (1.98 billion total ridership in 2018) (MTA, 2020), which potentially increases the risk of infection. NYC is also a high density city, with 84% of all housing units being multifamily housing and 11% of households living in overcrowded conditions (with more than one person per room) (U.S. U.S. Census Bureau, 2020; Furman Center for Real Estate and Urban Policy, 2010), which increase risks of infection and makes it difficult for people to follow the stay-at-home order, practice social distancing, and conduct quarantine.

NYC implemented its lockdown on March 23, 2020. Yet, the lockdown is partial, as non-essential workers are encouraged to work from home, while the public transit system continues to operate but with reduced schedules. Only after May 6, 2020, the subway system is shut down daily during 1–5 AM for cleaning. However, to compensate for the loss of subway service in the early morning, MTA added several hundreds of buses to its overnight routes to ensure access to public transit (Rose, 2020). While this partial lockdown may be less disruptive to economic activities, its effectiveness on mitigating the epidemic may be compromised when potentially infected persons can still ride the public transit (Smith, 2020; Tamman, 2020). However, GlAESer et al. (2020) argue that mobility reduction has the strongest effect in NYC than four other major cities in the U.S. especially at the early stages of the pandemic. Thus, NYC provides an ideal site to study how the mobility restriction policy together with the public transit system and other socioeconomic factors shape pandemic outcomes.

It would be ideal to compare public transit-oriented cities such as

1) Pandemic data: NYC Department of Health released COVID-19 infection cases and deaths for zip code zones. We use the accumulated cases and death tolls between April 6 and August 16, 2020 (starting two weeks after the implementation of lockdown policy with conventional two-week incubation period). This data is then 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: The number of subway stations and bus stops in each census tract is accessed through Metropolitan Transportation Authority (MTA) in NYC, which indicates 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 aggregated to the census tract level. SafeGraph provides many measures, such as the number of cellphones in the census block group, home census block group, number of visits to Point of Interests, median distance traveled from home, and median minimum dwell time in minutes. We use median time spent at home (minutes per day) during the pandemic and in the same period in 2019 (pre-pandemic period) to calculate mobility reduction during the pandemic. Considering the incubation period of symptoms, we use 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 conventional sociodemographic indicators at the census tract level.

Both non-spatial and spatial models are conducted to test the hypothesis. 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 explanatory variables include the following:

a) Stay-at-home indicator: This indicator measures the effectiveness of the lockdown and consequent mobility reduction in each census tract. Using SafeGraph 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 formula:

\[
\text{Stay-at-home indicator} = \frac{\text{Time at home in 2020} - \text{Time at home in 2019}}{\text{Time at home in 2019}} \times 100
\]

NYC with car-oriented cities such as Los Angeles and Houston. In general, mobility via cars is much less risky for infections than mobility via public transit, and we expect even more significant health disparities in car-oriented cities due to vastly different transport modes between subpopulation and neighborhoods. However, most cities, including Houston and Los Angeles, release only cumulative pandemic data at city/county level. Thus, the lack of detailed pandemic data prevents us from including different types of cities for comparison. However, the conceptual framework we develop is generalizable to any city as long as pandemic data at a smaller spatial scale is available.

As the pandemic evolves, the government shifts its focus from the lockdown in early 2020, to reopening in late 2020 and now to vaccination in 2021. This research focuses on “the lockdown period” (March 23rd–August 16th, 2020) when the lockdown was in place and before all four phases of reopening was implemented in NYC. Four types of data will be used, which are merged at the census tract level:

b) Transit station density: Number of stations (including bus stops and subway stations) per 10,000 people in each census tract. It measures accessibility to the public transit system and potential exposure to virus transmission and risks to infection.

c) Neighborhood socioeconomic variables: These variables at census tract level are chosen based on the framework of SDOH and data availability. They reflect the five key areas of SDOH as listed below.

A positive indicator means on average people in the census tract spent more time at home during the pandemic in 2020 than the same period in 2019, which indicates a reduced mobility after the lockdown. A negative indicator means on average people spent less time at home in 2020 than in 2019, and a zero indicates no change in mobility. The larger the indicator, the more effective the lockdown is.
Occupation is important to health disparities. However, the occupation category in ACS is too broad to be meaningful, thus it is not included. Instead, education is used.

1) Social and Community context: % of people aged 60+, household size, ethnic composition (%Blacks, %Asians, %Hispanics)
2) Economic stability: poverty rate
3) Education: % people with college+ education
4) Healthcare access: % people with no health insurance
5) Neighborhood and Built Environment: % using public transit

4. Results

4.1. Descriptive results

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 a relatively large standard deviation for both infection and death rate. Map 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). These “hotspots” are spread out in all five boroughs, 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 and Co-Op City in Bronx, and Flushing in Queens (Map 1).

The lockdown in NYC is generally effective. 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 spent 0–15% more time at home; in about 60% of census tracts, people spent 15–30% more time at home, and in about 13% census tracts, people spent 30% more time at home (Map 2). In other words, the effectiveness of lockdown varies across space, and people in most parts of the city followed the stay-at-home order. Only in about 3% of census tracts, people either spend less (0.53%) or the same amount of time (2.62%) at home in 2020, which implies that people in these census tracts did not seem to follow the 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, and Midwood in Brooklyn. Some of these census tracts may have a larger share of essential workers, and others such as those in Hasidic Jewish neighborhoods just did not follow the stay-at-home order for religious or other reasons.

LISA (Local Indicator of Spatial Association) in Map 3 demonstrates the spatial correlation between stay-at-home index and infection rate, death rate, respectively, and 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 are census tracts with high (low) stay-at-home index which are surrounded by tracts with high (low) infection/death rate, and the high-low (low-high) clusters are tracts with high (low) stay-at-home index which are surrounded by tracts with low (high) infection/death rate. The high-low clusters identify census tracts where staying-at-home is effective, while the high-high clusters are where the staying-at-home did not seem to work, and other factors may be shaping the infection and death that deserve further investigation.

4.2. Regression results

Both global models and GWRs are conducted to test hypotheses. Global models such as Gaussian and Poisson regressions are often adopted (e.g., Al Kindi et al., 2021; Lyanda et al., 2021; Wu & Zhang, 2021; Mollalo et al., 2020). We conducted both Gaussian and Poisson regressions, and Table 2 compares results. According to percent deviance explained and AICc, Gaussian model is much better than Poisson regressions. Thus, we adopt Gaussian model, and results are listed in Table 3. The model can explain about 48% of deviance in infection rate and 36% of deviance in death rate. The results clearly demonstrate the significant roles of stay-at-home order and public transit system even after controlling various socioeconomic variables. 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, the lower the infection and death rate for the census tract. With one percentage point increase in average time spent at home, infection rate decreases 0.056, and death rate decreases 0.046 (or 5.6 fewer infections and 4.6 fewer deaths per 1 million people). This clearly demonstrates the effectiveness of stay-at-home order. In contrast, the density of MTA stations has a positive and significant effect on both infection and death rate. With each additional stop per 10,000 people, infection and death rates are expected to increase 0.675 and 0.581 respectively (or 67.5 more infections and 58.1 more deaths per 1 million people). The shows the importance of the public transit system in pandemic outcomes.

In addition, ethnic composition is important. Both %Blacks and % Hispanics are positive and significant, meaning census tracts with a larger share of Blacks and Hispanics have higher infection and death rate. This is consistent with existing findings that these two ethnic groups are disproportionately affected by the pandemic (e.g., CDC, 2020b, APM Research Lab, 2020; Thebault et al., 2020). Interestingly, % Asians is significantly negative for infection rate but not significant for death rate. This shows census tracts with a larger share of Asians tend to have lower infection rates. With a long history of wearing masks in Asia for medical, environmental and cultural reasons (Jennings, 2020; Wong, 2020b) and the first COVID19 outbreak in China, Asian Americans are the first group to wear masks and take other precautions in the U.S. at the early stage of the pandemic, which may have contributed to their low infection rate. Not surprising, other socioeconomic factors also shape infection and death rate. Census tracts with larger average household size, a larger share of people 60+ years old and people with no insurance, and higher poverty rate have higher infection and death rate. In other words, census tracts with more disadvantaged and vulnerable population tend to have higher infection and death rates, which are expected.

There are two somewhat puzzling findings. First, %people taking public transit is not significant. However, this variable refers to the commute mode before the pandemic in 2018, not during the pandemic. Secondly, %people with college+ education has a positive and significant effect, even though its spearman correlations with outcome variables are negative. This means that after controlling all other variables in the model, census tracts with a higher share of people with college+ education have higher infection and death rate. While most professionals can work from home, educated healthcare workers often have to work in extremely risky environment during this pandemic. Healthcare industry in NYC is huge, and healthcare workers accounted for about 20% of all private employment in NYC, and about 7.8% of all healthcare workers in the U.S. (Teirlinck, 2020). This high concentration of healthcare workers in NYC may have contributed to this puzzling result. More research especially at the individual level, with commute mode during pandemic and detailed occupations, is needed to better understand these factors.

While Gaussian regressions reveal the overall relationship between

Table 1

| Occupation | 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 |
explanatory and outcome variables, it is a non-spatial/global regression, which assumes the effects of indicators are the same across space. GWRs are clearly better than non-spatial models, explaining 80% of deviance (Adjust $R^2$) in infection rate and 75% in death rate (Table 2). Summary statistics for GWR parameter estimates are listed in Appendix Table A1, and coefficients for some key variables are mapped in Maps 4–9.

According to Map 4, coefficients for stay-at-home index vary significantly across space for both infection and death rate. For most census tracts, coefficients are negative, 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 are mostly in the northern half of Staten Island, the north end of Manhattan, College Point and Far Rockaway area in Queens. In other words, these census tracts benefit the most from staying at home. However, in some census tracts, the coefficients are positive, which means spending more time at home is associated with higher infection and death rate. The highest positive coefficients are in northern Bronx (e.g., Riverdale, Inwood Washington Heights, Norwood, Bedford Park, Fordham, Mount Hope, and East Tremont), Brooklyn (e.g., Lindenwood), and Queens (e.g., Forest Hills). In addition to the lack of effectiveness of stay-at-home order, this demonstrates other factors may be more important in shaping pandemic outcomes in these census tracts. For example, much of these areas have a high concentration of Blacks and Hispanics. In Forest Hills neighborhood in Queens, the percentage of the elderly population is also very high (ranging between 33.5% and 50.9%). These sociodemographic factors may outperform the stay-at-home index in these areas.

Similarly, coefficients for MTA station density vary significantly across census tracts (Map 5). In census tracts with darker color, MTA station density has a larger positive effect on infection and death rate. These high coefficient clusters are mainly in Starrett City and Coney Island in Brooklyn, Flushing area in Queens, and Riverdale, Norwood, Co-op City in Bronx, and Harlem in Manhattan. With relatively a small number of subway stations in each census tract, MTA stations include mostly bus stops. These high impact areas are also neighborhoods with fewer subway lines/stations that rely heavily on buses for transport.

Maps 6–8 show the uneven impact of the concentration of ethnic minority population. On Map 6 for coefficients for %Asians, purple colors indicate census tracts with positive coefficients, meaning higher infection and death rate with higher percentages of Asians. The highest positive coefficients are located in Port Morris/Mott Haven/Long Wood in Bronx and Upper Westside and Harlem/Hamilton Heights/Manhattanville in Manhattan, and smaller positive coefficients are also located in Lower East Side/Chinatown/Lower Manhattan, Jackson Heights/East Elmhurst/Corona in Queens and Wingate and various parts in Brooklyn. 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 (e.g., Morrisania and Claremont Village), Brooklyn (e.g., Canarsie) and even Queens.

According to Map 7, %Blacks has positive effects in much of Staten Island, and various parts in Queens (e.g. Sunny side, Maspeth), Bronx (e.g. Riverdale), Manhattan (Midtown) and Brooklyn (e.g. Fort Hamilton, Bay Ridge, Dyker Heights), where a higher concentration of Blacks is associated with higher infection and death rate. Again, throughout NYC, there are census tracts with negative coefficients, where a higher concentration of Blacks is associated with lower infection and death rate, such as Harlem in Manhattan, Mott Haven and Longwood in Bronx, Flushing in Queens and Borough Park in Brooklyn.

Map 8 show the coefficients for %Hispanics, with high positive coefficients in Midtown/Clinton in Manhattan, various parts in Brooklyn (e.g. Canarsie, Red Hook), Bronx and Queens, and negative coefficients
in Staten Island, Far Rockaway in Brooklyn, College Points in Queens and the south end of Bronx. The patterns are largely similar to that for %Blacks, except Staten Island where %Hispanics has mostly negative coefficients while %Blacks has positive coefficients. In a borough with predominately non-Hispanic White (65%), it is interesting to see %Hispanics and %Blacks have different effects on pandemic outcomes at census tract level.

Map 9 displays coefficients for Percent of Population Aged 60+. The highest positive effects are in much of Staten Island, central and southern Brooklyn (e.g., Prospect Park, Coney Island), 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. This in part explains the high infect and death rates in Staten Island, a suburban borough.

In addition to the factor-specific clusters identified in Map 4–9, K-means Cluster Analysis is conducted with pandemic outcomes and all

### Table 2
Model comparison.

|                | Infection rate |      | Death rate |      |
|----------------|----------------|------|------------|------|
|                | Gaussian       | Poisson | GWR       | Gaussian | Poisson | GWR   |
| AIC            | 4532           | 89,964 | 2936       | 4928 | 15,767  | 3340 |
| AICc           | 4535           | 77,229 | 3191       | 4930 | 8101    | 3566 |
| R²/percent deviance explained | 0.478 | 0.233 | 0.843 | 0.367 | 0.206 | 0.805 |
| Adj. R²/percent deviance explained | 0.475 | 0.229 | 0.799 | 0.364 | 0.201 | 0.753 |

### Table 3
Gaussian regressions on infection and death rates.

| Variables                                      | Model 1: Infection rate |      | Model 2: Death rate |      |
|------------------------------------------------|-------------------------|------|---------------------|------|
|                                                | Estimate | SE   | p-Value             | Estimate | SE   | p-Value             |
| Intercept                                      | 0.000   | 0.016 | 1.000               | 0.000   | 0.018 | 1.000               |
| Stay-at-home indicator                         | -0.056  | 0.017 | ***                 | -0.046  | 0.019 | 0.016               |
| MTA stations per 10,000 people                | 0.675   | 0.016 | 0.001               | 0.581   | 0.018 | 0.000               |
| %Blacks                                       | 0.053   | 0.022 | **                  | 0.098   | 0.025 | 0.000               |
| %Asians                                       | -0.041  | 0.020 | **                  | -0.012  | 0.022 | 0.587               |
| %Hispanics                                    | 0.079   | 0.023 | ***                 | 0.063   | 0.026 | 0.014               |
| % People taking public transit                | -0.029  | 0.022 | ***                 | -0.002  | 0.024 | 0.933               |
| Poverty rate                                  | 0.061   | 0.023 | ***                 | 0.098   | 0.025 | 0.000               |
| % People aged 60                              | 0.086   | 0.020 | ***                 | 0.173   | 0.022 | 0.000               |
| % People with no health insurance             | 0.034   | 0.021 | *                   | 0.068   | 0.023 | 0.003               |
| Household size                                 | 0.095   | 0.024 | ***                 | 0.106   | 0.027 | 0.000               |
| % People with college+ education              | 0.056   | 0.031 | 0.069               | 0.091   | 0.034 | 0.007               |
| Residual sum of squares                       | 1076    |      |                     | 1304    |      |                     |
| Log-likelihood                                | -2254   |      |                     | -2452   |      |                     |
| AIC                                            | 4532    |      |                     | 4928    |      |                     |
| AICc                                           | 4535    |      |                     | 4930    |      |                     |
| R²                                            | 0.478   |      |                     | 0.367   |      |                     |
| Adj. R²                                        | 0.475   |      |                     | 0.364   |      |                     |

* p < 0.1.  
** p < 0.05.  
*** p < 0.01.
Map 4. GWR coefficients for stay-at-home index for census tracts.

Map 5. GWR coefficients for MTA stations per 10,000 people for census tracts

Map 6. GWR coefficients for Percent Asians for census tracts
significant variables identified in regression models. Five clusters with similar characteristics among census tracts are generated (Map 10), which can be considered “New Five Boroughs” based on COVID19 outcomes and other identified significant characteristics in census tracts. While most census tracts in each borough are similar to each other and belong to the same cluster, there are census tracts differ significantly from nearby census tracts and instead share similarities with those in other boroughs. For example, Staten Island mostly belongs to Cluster 2, but some tracts on the north shore are in Cluster 1, which includes census tracts mostly in Brooklyn, Queens and Bronx and is featured with a very high concentration of Blacks. On the other hand, some tracts in the other four boroughs are similar to those in Staten Island and belong to Cluster 2, which has the highest infection and death rate, yet, relatively low concentration of ethnic minorities and people without health insurance, low poverty rate, and lower density of MTA stations. However, Cluster 2 is featured with the highest share of people 60+ old and the lowest stay-at-home indicator among all 5 clusters. Cluster 3 has the second highest infection and death rate and is mostly in Bronx with a high concentration of Blacks and Hispanics, the highest poverty rate and people with no health insurance. Thus, despite high infection and death rate, Cluster 2 and Cluster 3 display different dynamics of the pandemic. This cluster analysis allows us to identify census tracts for further investigation and apply localized policy interventions.

5. Conclusions and discussion

As the end of 2021 approaching, the world continues to combat the COVID19 pandemic with some regions launching another new wave of lockdown. Yet, the impact of the unprecedented mobility restriction policies adopted in this pandemic is still largely unknown. This research studies the impact of municipal lockdown policy on intra-city health disparities in this pandemic, a well observed but under-studied phenomenon, by conducting a case study of NYC. This research expands the framework of SDOH from general health to infectious diseases, by focusing on factors shaping human mobility and thus infection risks that are key to pandemic outcomes. Theoretically, this research contributes to the literature on health disparities by identifying institutional sources of health disparities and the role of the government, through the lockdown and the transport infrastructure, in shaping health disparities in COVID19 pandemic. This research also enriches literature on mobility, transport, and the pandemic. Methodologically, the spatial approach adopted in this research not only is appropriate for infectious diseases but also reveals spatial complexities in the patterns of health disparities and their dynamics that non-spatial methods cannot. Findings also have
Several findings can be highlighted here. First, there are significant spatial disparities in both infection and death rate at the census tract level. This intra-city health disparities complicate pandemic outcomes, and a multilevel perspective is needed to better understand health disparities at different spatial levels (national/regional/city/neighborhood). There are some “hotspot” neighborhoods with very high infection and death rates, which may have very different dynamics as indicated by the cluster analysis, and further investigation is needed to better understand the detailed mechanisms for their infection and death rates, especially micro-level behavioral and environmental factors that cannot be revealed in this aggregated analysis at census tract level. Secondly, the lockdown is effective in lowering infection and death rate at the census tract level, which is consistent with other studies (e.g., Chang et al., 2021; Glaeser et al., 2020; Noland, 2021). This offers strong evidence for the need for a lockdown policy during pandemics, despite strong pushbacks from some people in COVID19 pandemic. While a strict lock-down as China implemented in Wuhan is probably impossible in most cities in the West, the government can make it easier for people to comply with the lockdown policy by better educating the public about the importance of lockdown and by reducing the digital divide. However, the effect of lockdown policy in NYC varies significantly across neighborhoods, contributing to large disparities in pandemic outcomes. This reflects neighborhood differences in willingness and capability in policy compliance, which shows that location-specific policy interventions might be needed in future pandemics to be more effective and to reduce health disparities. In addition, for global cities such as NYC, international and regional mobility needs to be considered as well for more effective intervention. As Li et al. (2020) suggest that a hierarchical intervention strategy with global collaboration and localized policies targeting high risk areas can be the most effective.

Thirdly, public transit system plays an important role in pandemic outcomes, and its uneven accessibility across space contributes to health disparities. In general, the higher density of transit stations a census tract has, the higher the infection and death rate are. The density of transit

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**Map 9.** GWR coefficients for Percent of Population Aged 60+.

**Map 10.** K-means Cluster Analysis: New Five Boroughs.
stations is an indirect measure for the demand for and the actual ridership on public transit. Census tracts with a higher density of transit stations likely have disadvantaged population that rely on public transit for work and other daily activities. Thus, instead of shutting down transit stations, alternative measures that are proven to be effective should be used to mitigate pandemic outcomes, which include reducing crowding in public transport, mandatory mask wearing on transit, and enhanced hygiene and ventilation standards (Tirchini & Cats, 2020; Jiang et al., 2020; van Doremalen et al., 2020; CDC, 2020a, 2020b, 2020c). Transportation planning and policies in the U.S. have historically favored highways and rails for suburban commuters instead of public transit for urban predominantly ethnic minorities and low-income residents, which has resulted in many negative socio and economic impact on the latter (Sanchez, Brenman, Ma, & Stolz, 2018; Sanchez, Stolz, & Ma, 2003). In addition to addressing socioeconomic inequality, future transport planning should also consider the role of transport system in pandemics and how to promote health equity.

Fourthly, neighborhood socioeconomic indicators are important in shaping pandemic outcomes and contribute to health disparities across space. Census tracts with a higher concentration of disadvantaged population, such as Blacks, Hispanics, the elderly, the poor, people with no health insurance, and larger households have higher infection and death rates. This is consistent with the literature on SDOH. However, the concentration of Asians is found to be negatively associated with infection rate and not significant for death rate. Asians in NYC are among the first people to protect themselves by wearing masks. However, detailed micro-level analysis is needed to understand why Asian communities have the opposite outcomes from other ethnic communities. In addition, the effects of these socioeconomic factors vary across space and high risk neighborhoods can be identified for localized policies and neighborhood specific support, which might be more effective in mitigating pandemic outcomes and minimizing impact on vulnerable neighborhoods and subpopulations.

This research is limited in several ways, which demands further research. First, mobility reduction is measured using cell phone data on time spent at home and outside. While it is a good measure for stay-at-home order, it cannot differentiate risker mobility (e.g., taking public transit to a grocery store) from safer mobility (e.g., driving or walking to a park with limited risk of infection). Subway turnstile data is available for NYC, but mobility through bus, driving, and walking is not. A large part of NYC relies on bus, and driving is more dominant in Staten Island. Thus, subway turnstile data is not ideal either. The number of transit stations used in this study is a proxy and only an indirect measure for ridership and mobility. It is important for future studies to investigate the association between actual public transit ridership during this pandemic and infection and death rates. A better measurement for mobility and comparison of different kinds of mobility data are needed. Second, transit station density measures only one aspect of the mobility infrastructure. Other aspects such as how subway and bus lines and stations/stops are connected might be important and a better measurement for the public transit system is needed. In addition to public transport system, mobility infrastructure in NYC includes the taxi system and private cars, which need to be considered as well when data is available. Regional and international mobility via regional trains and airports are also important especially for global cities and transportation hubs (Musselwhite et al., 2020). Thirdly, as indicated in our multilevel conceptual framework, individual/household level factors such as SES indicators and policy compliance affect pandemic outcomes. However, due to the lack of individual level data, micro-level analysis is impossible at this stage.

Finally, cities with different transport systems (e.g. car oriented vs. public transit) and different governance styles (authoritarian vs. democratic) may have different dynamics. We anticipate the role of public transport in cities such as Los Angeles and the role of lockdown policy in cities such as Wuhan, China will be very different from NYC. Comparative research is needed when data is available. Despite these limitations, this research contributes significantly to the understanding of health disparities in pandemics by offering a perspective of mobility and by identifying the institutional roots for health disparities, through examining the roles of mobility reduction policy and the public transport system. Both have significant policy implications. The focus on intra-city health disparities in this pandemic further enriches the literature that is currently focused more on national and regional health disparities.

CRediT authorship contribution statement

Youqin Huang: Conceptualization, Methodology, Writing – original draft, Writing – review & editing. Rui Li: Methodology, Formal analysis, Visualization, Resources.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Appendix Table A1

Summary statistics for GWR parameter estimates for infection and death rate.

| Variable | GWR1: Infection rate | GWR2: Death rate |
|----------|----------------------|------------------|
|          | Mean   | STD    | Min    | Median | Max    | Mean   | STD    | Min    | Median | Max    |
| Intercept| 0.022  | 0.505  | −1.612 | −0.009 | 3.032  | 0.053  | 0.520  | −2.259 | 0.028  | 2.824  |
| Stay-at-home indicator | −0.046 | 0.127  | −0.422 | −0.034 | 0.306  | −0.043 | 0.135  | −0.672 | −0.025 | 0.457  |
| MTA stations per 10,000 people | 0.737  | 0.557  | −0.037 | 0.539  | 2.654  | 0.745  | 0.573  | −0.465 | 0.544  | 2.618  |
| % Black | 0.144  | 0.490  | −1.334 | 0.041  | 3.847  | 0.152  | 0.475  | −2.114 | 0.098  | 2.686  |
| % Asian | −0.056 | 0.283  | −1.214 | −0.021 | 1.697  | −0.046 | 0.311  | −1.680 | 0.001  | 1.988  |
| % Hispanic | 0.027  | 0.232  | −1.014 | 0.030  | 0.846  | 0.055  | 0.259  | −0.956 | 0.051  | 1.135  |
| % People taking public transit | −0.084 | 0.156  | −1.082 | −0.067 | 0.308  | −0.071 | 0.149  | −0.787 | −0.049 | 0.315  |
| Poverty rate | −0.003 | 0.161  | −0.592 | 0.005  | 0.455  | 0.014  | 0.173  | −0.986 | 0.005  | 0.660  |
| % People aged 60+ | 0.039  | 0.183  | −1.145 | 0.028  | 0.658  | 0.076  | 0.204  | −1.023 | 0.055  | 0.623  |
| % People with no health insurance | 0.021  | 0.109  | −0.553 | 0.019  | 0.610  | 0.031  | 0.111  | −0.379 | 0.031  | 0.566  |
| Household size | 0.024  | 0.265  | −1.330 | 0.038  | 1.248  | 0.042  | 0.269  | −1.279 | 0.044  | 1.207  |

(continued on next page)
Appendix Table A1 (continued)

| Variable                                      | GW1: Infection rate | GW2: Death rate |
|-----------------------------------------------|---------------------|-----------------|
| % People with college - education             | 0.083 0.263         | 0.068 1.133     |
| Residual sum of squares                       | 323                 | 403             |
| Effective number of parameters (trace(S))     | 451                 |                 |
| Degree of freedom (n – trace(S))              | 1609                | 1632            |
| Sigma estimate                                | 0.448               | 0.497           |
| Log-likelihood                                | –101.379            | –0.497          |
| Degree of dependency (DoD)                    | 0.525               | 0.532           |
| AIC                                           | 2936                | 3340            |
| AICc                                          | 3191                | 3566            |
| BIC                                           | 5482                | 5754            |
| R²                                            | 0.843               | 0.805           |
| Adj. R²                                       | 0.799               | 0.753           |
| Adj. alpha (95%)                              | 0.001               | 0.001           |
| Adj. critical t value (95%)                   | 3.214               | 3.198           |

References

Al Kindi, K. M., Al-Mawali, A., Alkharsu, A., Alshukaili, D., Alnasiri, N., Al-Awadhi, T., El Azar, K. M., Shen, Z., Romanelli, R. J., Lockhart, S. H., Smits, K., Robinson, S., & Banister, D. (2018). Bajardi, P., Poletto, C., Ramasco, J. J., Tizzoni, M., Colizza, V., & Vespignani, A. (2011). Chen, J. T., Waterman, P. D., Krieger, N., & Krieger, N. (2020). Bonow, R. O., Fonarow, G. C., & O

CDC. (2020). Social determinants of health. https://www.cdc.gov/socialdeterminants/

Bonner, R. O., Fonarow, G. C., O

Gargoum, S., & Gargoum, A. S. (2021). Limiting mobility during COVID-19, when and to what level? An international comparative study using change point analysis. Journal of Transport & Health, 20, Article 101019. https://doi.org/10.1016/j.

Garcia, V., Zangelin, A., Zanella, A., et al. (2020). Baseline characteristics and outcomes of 1591 patients infected with SARS-CoV-2 admitted to ICUs of the Lombardy Region, Italy. JAMA Cardiol. https://doi.org/10.1001/jamacardio.2020.1105. Published online March 27.

Gosch, L., & Johansson, A. (2018). Analysing the link between public transport use and airborne transmission: Mobility and contagion in the London underground. Environmental Health, 17(1), 84.

Harris, J. (2020). The subways seeded the massive Coronavirus epidemic in New York City, NBER working paper no. 27021.

Jia, J., Ding, J., Liu, S., Li, G., Li, J., Du, B., ... & Zhang, B. (2020). The control of COVID-19: impact of policy interventions and meteorological factors. arXiv preprint arXiv:2003.02985.

Jiang, F., Jiang, X., Wang, Z., Meng, Z., Shao, S., Anderson, B. D., & Ma, M. (2020). Detection of severe acute respiratory syndrome coronavirus 2 RNA on surfaces in quarantine rooms. May 21 Emerging Infectious Diseases, 26(9), 2162-2164. https://doi.org/10.3201/eid2609.201485.

Jennings, R. (2020). Not just coronavirus: Asians have worn face masks for decades. bit

Kawrda, G., & Sakamoto, K. (2021). Spatialising urban health vulnerability: An analysis of NYC’s critical infrastructure during COVID-19. Urban Studies, 0426709521104304. Published online first on Oct. 1st, 2021.

Kermack, W. O., & McKendrick, A. G. (1927). A contribution to the mathematical theory of epidemics. Proceedings of the Royal Society of London, Series A, 115(772), 700–721. Contains papers of a mathematical and physical character.

Lai, S., Ruktanonchai, N. W., Zhou, L., Prosper, O., Luo, W., Floyd, J. R., & Tatem, A. J. (2020). Effect of non-pharmaceutical interventions for containing the COVID-19 outbreak in China. Nature, 585, 410-413. https://doi.org/10.1038/s41586-020-2293-x

Lee, V. J., Chiew, C. J., & Khong, W. X. (2020). Interrupting transmission of COVID-19: Lessons from containment efforts in Singapore. Journal of Travel Medicine, 27(3), Article taaa359.

Li, T., Dodson, J., & Sipe, N. (2015). Differentiating metropolitan transport disadvantage by mode: Household expenditure on private vehicle fuel and public transport fares in Brisbane, Australia. Journal of Transport Geography, 49, 16-25.

Li, R., Chen, B., Zhang, T., Ren, Z., Song, Y., Xiao, Y., Xu, B., ... (2020). Global COVID-19 pandemic demands joint interventions for the suppression of future waves. Proceedings of the National Academy of Sciences, 117(42), 26151-26157.

Liao TF, De Maio F. (2021). Association of social and economic inequality with coronavirus disease 2019 incidence and mortality across US counties. JAMA network open. 2021;4(1): e2034578-e2034578.
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Cities 122 (2022) 103549

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Leslie, D., Mazumder, A., Peppin, A., Wolters, M. K., & Hagerty, A. (2021). Does “AI” stand for augmenting inequality in the era of covid-19 healthcare? BMJ, 372.

Lyanda, A. E., Bokev, K. A., Liu, Y., & Oppong, J. R. (2021). Racial/Ethnic heterogeneity and rural-urban disparity of COVID-19 case fatality ratio in the USA: A negative binomial and GIS-based analysis. Journal of Racial and Ethnic Health Disparities, 1–14.

Marmot, M., & Wilkinson, R. (Eds.). (2005). Social determinants of health. Oxford, Oxford: Oup, McLaren, J. (2021). Racial disparity in COVID-19 deaths: Seeking economic roots with census data. The BE Journal of Economic Analysis & Policy. April 30.

Meeker, J. K. (2020). The political nightmare of the plague: The ironic resistance of anti-quarantine protesters. In COVID-19 (pp. 109–121). Routledge.

Mein, S. A. (2020). COVID-19 and health disparities: The reality of ‘the great equalizer’. Journal of General Internal Medicine, 35(8), 2439–2440. https://doi.org/10.1007/s11606-020-05880-5

Metropolitan Transportation Authority (MTA). (2020). Letter from Chairman Patrick J. Foye to Senator Charles E. Schumer and Congresswoman Nia Lowey, April 16, 2020.

Mollao, A., Vahedi, B., & Rivera, K. M. (2020). GIS-based spatial modeling of COVID-19 incidence rate in the continental United States. Science of the Total Environment, 728, Article 138864.

Moore, J. T., Pilkington, W., & Kumar, D. (Oct 2020). Diseases with health disparities as drivers of COVID-19 outcome. Journal of Cellular and Molecular Medicine, 24(19), 11038–11045.

Musselwhite, C., Avineri, E., & Susilo, Y. J. J. (2020). In The right to transportation: Augmenting inequality in the era of COVID-19 healthcare? (pp. 1–40). https://doi.org/10.1289/EHP8631

Munn, K. (2021). The Inaugural Munn Distinguished Lecture: economic inequality and determinants of health on the emerging COVID-19 pandemic in the United States. doi.org/10.1001/jamacardio.2020.0950

Peiris, J. M., & Guan, Y. (2004). Confronting SARS: A view from Hong Kong. Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences, 359(1447), 1075–1079.

Pyle, G. F. (1969). The diffusion of cholera in the United States in the nineteenth century. Geographical Analysis, 1(1), 59–75.

Qiu, Y., Chen, X., & Shi, W. (2020). Impacts of social and economic factors on the transmission of coronavirus disease 2019 (COVID-19) in China. Journal of Population Economics, 1, 2053. https://doi.org/10.1007/s10813-020-00575-8

Rose, A. (2020). For the first time in its history, New York City deliberately shut down its entire subway system this morning. May, 6. CNN https://www.cnn.com/2020/05/06/us/new-york-subway-closed-historical-first/index.html.

Rynchev, L. A., & Longini, I. M., Jr. (1985). A mathematical model for the global spread of influenza. Mathematical Biosciences, 75(1), 3–22.

Ren, X. (2020). Pandemic and lockdown: a territorial approach to COVID-19 in China, Italy and the United States. Eurasian Geography and Economics, 61(4–5), 423–434.

SafeGraph. (2020). Social distancing metrics. SafeGraph. https://docs.safegraph.com/docs/social-distancing-metrics,

Sanchez, T. W., Stolz, R., & Ma, J. S. (2020). Moving to equity: Addressing inequitable effects of transportation policies on minorities. Cambridge, MA: The Civil Rights Project at Harvard University.

Sanchez, T. W., Breman, M., Ma, J. S., & Stolz, R. H. (2018). The right to transportation: Moving to equity. Routledge.

Shepherd, M. (2020). Why geography is a key part of fighting the COVID-19 coronavirus outbreak. April 15. Forbes https://www.forbes.com/sites/marshallshepherd/2020/03/05/why-the-discipline-of-geography-is-a-key-part-of-the-coronavirus-outbreak/.

Shi, S., Qin, M., Shen, B., et al. (2020). Association of cardiac injury with mortality in hospitalized patients with COVID-19 in Wuhan, China. JAMA Cardiology. https://doi.org/10.1001/jamacardio.2020.0950

Singh, S., Acharya, A., Challagundla, K., & Byrareddy, S. N. (2020). Impact of social determinants of health on the emerging COVID-19 pandemic in the United States. Frontiers in Public Health, 8, 417–424.