The unequal impact of COVID-19: An analysis of mobility behaviors of socially vulnerable populations

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Keywords: COVID-19, health inequity, human mobility, social justice, social vulnerability, spatial non-stationarity

Introduction

Various policies to limit people's mobility such as restricting travels, working from home, and closing nonessential business have been implemented to mitigate the spread of the coronavirus disease 2019 (COVID-19). However, little has been done to understand what adverse effects these policies may have on socially vulnerable populations who are put more at risk of being exposed to COVID-19 due to their socioeconomic status and inability to work from home. Recent studies have revealed health inequity and social injustice in the impact of COVID-19 in terms of cases and deaths (Karaye & Horney, 2020; Khazanchi et al., 2020). Further studies have shown the disproportionate impact of COVID-19 on low income (Weill et al., 2020), Blacks (Gaynor & Wilson, 2020), and immigrants groups (Clark et al., 2020), and these inequities vary significantly between different neighborhoods (Coelho et al., 2020; Mansour et al., 2021; Sannigrahi et al., 2020). These inequities have been linked with not only the socio-demographic composition but also the urban and rural divide (Khazanchi et al., 2020). To advance our understanding of these inequities, there is a need to consider these population groups and their neighborhoods within the lens of human activity and mobility behaviors. To estimate the unequal exposure to COVID-19, existing studies have used mobility measures such as home-dwelling times (Fu & Zhai, 2021; Hu et al., 2022; Huang et al., 2022) and travel distances (Iio et al., 2021) from anonymous mobile phone location data. However, these measures still capture the static notions of population behavior like any other census demographics and disregard the connectivity and spatial structural patterns embedded within the network of human mobility. A few studies have used mobility measures to reveal structural patterns in mobility data (Iio et al., 2021; Pepe et al., 2020; Wang & Taylor, 2016), but they fail to consider the patterns of different socio-economic classes, which exhibit substantial geographical variation.

In this study, we investigate how mobility of population groups with varying social vulnerability has changed in response to COVID-19 as a natural experiment. We adopt and develop a series of network-based mobility measures to reveal spatial non-stationarity (geographical variation) in the relationship between social vulnerability and mobility behaviors. To estimate the changes of people's mobility, we first develop a mobility indicator, Outflow-Weighted Radius of Gyration (OWRg), that measures how far people travel from a neighborhood to other neighborhoods across the country. Second, we compute mobility change of each tract by comparing its OWRg of pre-pandemic to OWRg of lockdown period. Finally, we apply the bivariate local indicators of spatial association (LISA) method to identify the local associations between mobility changes and social vulnerability. We use census tracts in two most populated Metropolitan Statistical Areas (MSAs) in the U.S.: New York and Los Angeles. Our results reveal distinct human mobility patterns. On one hand, we identified geographic clusters of neighborhoods that have high social vulnerability and unchanged or increased mobility. On the other hand, we identified neighborhoods that have low social vulnerability and significantly decreased human mobility patterns. We also identified outlier neighborhoods in which high or low social vulnerability were associated with low or high mobility patterns.

Method

Data processing

We use two most populated MSAs in the U.S., New York-Newark-Jersey City, NY-NJ-PA (NY MSA, hereafter) and Los Angeles-Long Beach-Anaheim, CA (LA MSA, hereafter) as our case study areas at the census tract level. We limit the temporal extent to 2020/01/01 – 2020/02/29 as the pre-pandemic period and 2020/04/01 – 2020/05/31 as the lockdown period. Using mobile phone location data provided by SafeGraph (SafeGraph, 2020), we extract human mobility between every pair of tracts by estimating the daily number of visitors from one tract to another (Kwon et al., 2021). In this study, we limit origin tracts to the tracts in our study area but include all destination tracts in the contiguous U.S. To estimate social vulnerability of each tract, we use Social Vulnerability Index (SVI) provided by Centers for Disease Control and Prevention (CDC). CDC's SVI provides the relative vulnerability of each tract in the U.S estimated by considering socioeconomic and demographic factors including income, age, race, housing type, and transportation availability (Flanagan et al., 2011).

Estimating the changes in human mobility

Despite our plan to evaluate a series of mobility measures, in this paper, we only report the results of OWRg, which measures the spatial range of human mobility from each origin by considering the volume of outflow to each destination as the weight of an edge. OWRg is modified from Radius of gyration (Rg), commonly used in the literature to measure the range of mobility (Pepe et al., 2020; Y. Xu et al., 2018). Different from Rg, OWRg is measured for each neighborhood (tract) by calculating the weighted mean center of the total volume of outflows from an origin to each destination. By using weighted mean center, we reduce the bias introduced by far destinations with only a few visitors. OWRg is defined as follows:

$$WR_g(i) = \sqrt{\frac{\sum_{j=1}^{n}(d_j - l_{wc})^2}{n}}$$

For each origin tract i: d_j is the location of destination d_j, n is the number of destinations, and d_{wc} is the weighted mean center of all destinations. d_{wc} is calculated by summing the product of the coordinates and the number of visitors of each of all destinations and then dividing this sum by the total number of visitors to all destinations. Finally, we estimate the change of OWRg for each tract by subtracting its OWRg during the pre-pandemic period from its OWRg during the lockdown period.

Capturing local associations between mobility change and social vulnerability

We use bivariate LISA statistic to capture spatial non-stationarity in the relationship between mobility change and social vulnerability. Bivariate LISA identifies local associations between the value for one variable of a tract and the average of the surrounding values for another variable of the surrounding tracts (Anselin, 1995). Bivariate LISA returns four types of clusters whose name indicates the value of the first variable and that of second variable: High-High, High-Low, Low-High, Low-Low. In this study, bivariate LISA captures if social vulnerability of one tract is surrounded by high or low level of mobility changes.

Results

We first estimate mobility changes from the pre-pandemic period to the lockdown period for each tract. Since mobility measure in this study indicates the spatial range of people’s traveling, a negative value of mobility changes means that the spatial range of mobility has been reduced. As Figure 1 shows, most tracts decreased their mobility in response to COVID-19 and the mitigation policies, however, there are some neighborhoods whose mobility increased as marked on Figure 1 with circles.

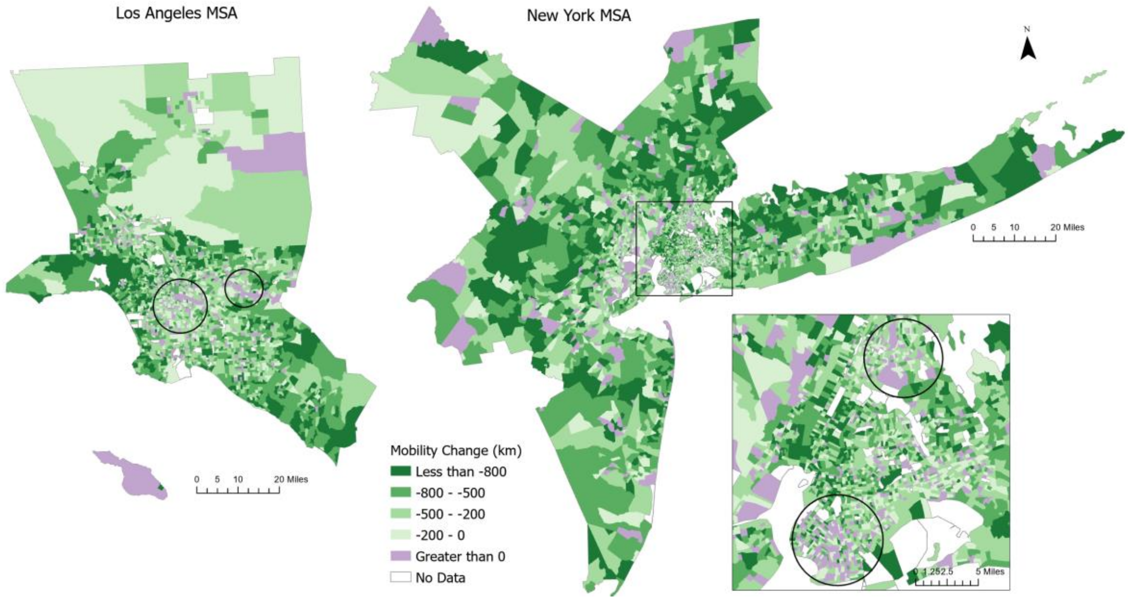

Figure 1. Mobility changes in response to COVID-19 at tract level.

Bivariate LISA reveals four clusters of local associations decided by the level of social vulnerability compared to mobility changes in the surrounding neighborhoods (Figure 2). Note that mobility change here is the value of change in mobility range, and negative value means decrease, as two histograms in Figure 2 illustrate. So, if one tract falls into the low-low cluster, it means that social vulnerability of this tract is low, and its surrounding tracts decreased their mobility significantly. In both of the two MSAs, High-High and Low-Low clusters are predominant. The tracts with high social vulnerability are spatially correlated and surrounded by the tracts that exhibit little or no change or even increase in mobility (red clusters). On the other hand, the tracts with low social vulnerability are surrounded by the tracts with substantial decrease in mobility (blue clusters). This implies that people with high social vulnerability sustained similar or more mobility during the lockdown period, which made them more likely to be infected by the virus. These results not only confirm the previous findings that less vulnerable populations have decreased their mobility significantly more than more vulnerable populations (Borkowski et al., 2021; Weill et al., 2020) but also reveal the geographic variations in these relationships between social vulnerability and mobility changes.

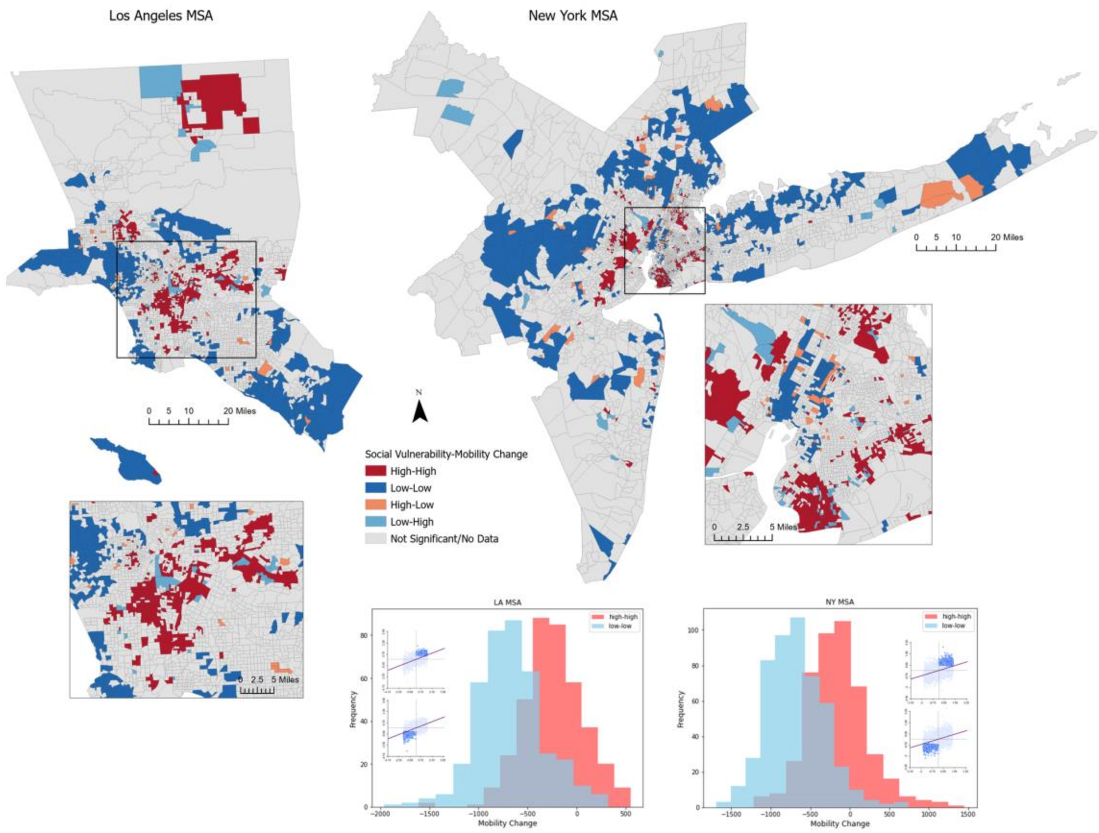

Figure 2 Spatial associations between social vulnerability and mobility changes

Discussion and Conclusion

Our study reveals varying spatial associations between social vulnerability and the changes in human mobility behaviors. Particularly, the results highlight the neighborhoods with high social vulnerability and incapability of decreasing mobility activities despite the existing policies to reduce mobility, which shows disproportionate risk of being exposed to COVID-19. However, our study has some limitations, which we plan to address in the near future. First, due to the exploratory nature of bivariate LISA, we are unable to ascertain why these varying associations exist. So, we plan to examine the factors that affect human mobility behaviors during disruptive events. Moreover, different mobility indices may produce different results (Noi et al., 2022). To avoid bias from indices, we plan to evaluate a series of mobility measures such as entropy (Koylu & Guo, 2013), exposure indices (W. Xu, 2022), median distance travelled (Noi et al., 2022), travel diversity (Y. Xu et al., 2018), clustering coefficient, and netflow ratio. These measures will help identify how different mobility measures affect the results and reveal structural mobility patterns. The results of this work will help identify neighborhoods that have distinct mobility behaviors in accordance with varying levels of social vulnerability of their residences and improve our understanding of complex issues of social justice and health inequity.

Acknowledgement

We thank Beichen Tian for the initial processing of the SafeGraph mobility data.

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