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SUPPLEMENT ARTICLE

Population Mobility and Aging Accelerate the Transmission of Coronavirus Disease 2019 in the Deep South: A County-Level Longitudinal Analysis

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Population mobility and aging at local areas contributed to the geospatial disparities in the coronavirus disease 2019 (COVID-19) transmission among 418 counties in the Deep South. In predicting the incidence of COVID-19, a significant interaction was found between mobility and the proportion of older adults. Effective disease control measures should be tailored to vulnerable communities.

Keywords. COVID-19; Deep South; Disparities; Incidence; Population mobility.

The coronavirus disease 2019 (COVID-19) pandemic threatens population health and increases the healthcare burden. Although nonpharmaceutical interventions and vaccination have been implemented to curb the COVID-19 transmission, progress in controlling disease spread has been slow. After the early reopening policies implemented in June 2020, transmission across the nation accelerated quickly, especially in the Deep South, such as Alabama, Georgia, Louisiana, Mississippi, and South Carolina. By 5 November 2021, the average incidence rate among these 5 Deep South states was 16 672 per 100 000, as higher than in New York (13 115 per 100 000) or California (12 475 per 100 000). Given the rapid spread of COVID-19 in the Deep South, it is worth investigating the potential contextual factors contributing to the spread.

Age disparities were found in COVID-19–related health outcomes. At the individual level, older adults have high rates of COVID-19–related infection, hospitalization, and death, potentially owing to underlying medical conditions, such as hypertension, diabetes, cardiovascular disease, and respiratory diseases [1]. At the population level, age composition is closely associated with vulnerability to COVID-19 outbreak, with regions with a larger proportion of older adults experiencing a higher incidence of COVID-19 [2, 3].

Population mobility is closely associated with COVID-19 outbreak. Mobility estimated by digital devices could proximally reflect both positive and negative influences of nonpharmaceutical interventions, reopening actions, and public holidays [4, 5]. Digital-based mobility data have been used to predicting the incidence of COVID-19 [6]. However, there is a dearth of data regarding the interaction between population mobility and the proportion of older adults at local areas. Therefore, we sought to examine the effects of population mobility and proportion of older adults on COVID-19 incidence and test whether the interaction between these factors was significant in predicting COVID-19 outbreak in the Deep South. The findings of this study could inform tailored disease control measures for vulnerable communities.

METHODS

We conducted an ecological study at the population level by integrating disease surveillance data, digital-based population mobility, and county-level factors from multiple public data sets across the 418 counties of 5 Deep South states (ie, Alabama, Georgia, Louisiana, Mississippi, and South Carolina) from March 2020 to January 2021. The study protocol was approved by the institutional review board at the University of South Carolina. Biweekly cumulative confirmed cases of COVID-19 in each county were retrieved from the US health data [7]. The first time point was decided based on the first COVID-19 diagnosis in each state, and a total of 24 time points by 2-week intervals were used for analysis. Biweekly

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COVID-19 new cases were calculated by subtracting the cumulative confirmed cases of previous time point from the total cases.

We extracted daily population flows through social distancing metrics data from SafeGraph, a commercial company that creates population foot-traffic data, such as visitor counts, dwell times, distance traveled, and visitor origins at the census block group level, obtained using a panel of global positioning system pings from nearly 10% of anonymous mobile devices in the United States [8, 9]. SafeGraph mobility data have good representativeness, including for rural areas, in terms of population distribution and demographic characteristics at the county level [8, 9]. Prior research confirmed that SafeGraph mobility data could identify at-risk population and adequately predict future COVID-19 incidence among racially and socioeconomically disadvantaged communities [10]. SafeGraph mobility data were used to calculate the population mobility within and across the counties for each time point [8, 9].

We obtained the proportion of older adults (aged ≥65 years) at each county from the 2019 American Community Survey. Other county-level covariates were defined according to the existing literature on the structural and social determinants of racial/ethnic disparities in COVID-19 outbreak [11]. Thakur and colleagues [11] proposed that racism, social class, and social stratification shaped the risk of exposure to COVID-19 through (1) occupation and transportation; (2) housing, crowding, and resource access; and (3) insurance and healthcare resources [9]. Based on this conceptual framework, county-level covariates were organized into 4 dimensions, including as demographic characteristics (eg, population density, proportion of Black residents, Gini index), healthcare access and susceptibility (eg, percentage of people without health insurance, primary care provider rate [number per 100 000 population], and percentage of adults reporting fair or poor health), housing and neighborhood environment (eg, crowding and percentage of rental housing), and transportation (eg, accessibility of transportation and means of transportation for commuting to work) [11–13]. Supplementary Table 1 in Supplement 1 shows the detailed descriptions and definitions of all proposed county-level factors.

The spatiotemporal trends of COVID-19 incidence and population mobility were described using geospatial mapping. Poisson mixed regression was used to investigate the associations among COVID-19 incidence, population mobility, and the proportion of older adults, adjusting for the time effect, cluster effect, and county-level covariates. The cluster effect of state was accounted as a random term, and population density was used as an offset term to standardize COVID-19 incidence. We used stepwise selection to identify variables with potential impact on changes in COVID-19 incidence. Interaction between population mobility and the proportion of older adults was further examined.

RESULTS

Overall, the county-level COVID-19 incidence increased during the time window of the study. Geospatial disparities in COVID-19 incidence were found in each state across the selected time points. Population mobility within and across the counties also displayed spatiotemporal trends. Generally, counties with more internal population mobility experienced higher COVID-19 incidence over time. Supplementary Figures 1A–1C in Supplement 2 shows the geospatial distribution of COVID-19 incidence and digital-based population mobility at each selected time point.

Among the initial 20 county-level factors, only 6 (ie, proportion of older adults, public assistance, Gini index, accessibility of transportation, use of public transportation to commute to work, and population mobility within county) were retained in the final model by stepwise selection. Population mobility was positively associated with COVID-19 incidence (β = .174 [95% confidence interval, .117–.231]) while the proportion of older adults did not show a significant effect (β = .061; [–.019 to.141]). A significant interaction was found between the proportion of older adults and population mobility (β = .055 [95% confidence interval, .002–.108]). This finding implied that population mobility increased the county-level COVID-19 incidence, especially for counties with a large proportion of older adults. Table 1 shows the results of multivariable analysis, and Supplementary Figure 2 in Supplement 3 shows the effects of population mobility on COVID-19 incidence by the proportion of older adults.

DISCUSSION

Leveraging aggregated data and geospatial mapping, we examined the association between population mobility and COVID-19 incidence and the difference in this association by proportion of older adults in the Deep South. Geospatial disparities of COVID-19 outbreak were identified. Population

Table 1. Poisson Mixed Models of County-Level Coronavirus Disease 2019 Incidence in the Deep South

	Model 1[a]	Model 2[a]
Factors	β (95% CI)	β (95% CI)
Time point	.115 (.109–.120)[b]	.115 (.109–.120)[b]
County-level factors		
Proportion of older adults	.079 (–.004 to .161)	.061 (–.019 to .141)
Population mobility within county	.154 (.091–.217)[b]	.174 (.117–.231)[b]
Interaction between proportion of older adults and population mobility within county	…	.055 (.002–.108)[c]

Abbreviation: CI, confidence interval.

[a]Public assistance, Gini index, transportation accessibility, and use of public transportation to commute to work were controlled for in both models 1 and 2.

[b]$P < .001$.

[c]$P < .05$.

mobility within the county contributed to these disparities. The impact of population mobility on the county-level COVID-19 incidence became stronger among counties with a larger proportion of older adults. Our study provided new insights on the use of digital data in COVID-19 research, and our findings have implications for future structural and policy efforts to control disease among vulnerable communities.

At the early stage of the pandemic, county-level COVID-19 transmission was accelerated by population mobility [6]. Social distancing or travel restrictions was an important strategy to prevent the initial COVID-19 outbreak [14]. In addition, we found that the positive effect of population mobility on COVID-19 incidence increased among counties with a larger proportion of older adults. This finding suggested that social distancing or travel restriction was critically important among an older and vulnerable community. Policies regarding social distancing or travel restrictions might be effective in mitigating COVID-19 by reducing population mobility at the state and county levels, especially during the early stage of the pandemic when vaccination was not widely available [14]. However, these policies might also have substantial costs in economics and resources access. Continuous preventive measures with consideration of individual mitigation measures (eg, testing, vaccination, and face masking) among vulnerable communities may be effective in controlling the COVID-19 pandemic and could avoid or reduce any adverse social and economic costs of reduced mobility [14].

The current study has several limitations. First, this was an ecological study, and the findings might suffer from ecological fallacy. Second, although >60% of older adults in the United States own a smartphone [15], estimating population mobility using mobile devices may introduce a bias against older adults, who are less likely to have mobile devices than young people. Third, population mobility did not differentiate among social events at different locations, such as parks, workplaces, and retail locations, which may have different effects on COVID-19 incidence. Finally, although we selected county-level covariates based on an existing conceptual framework, other county-level factors that were not controlled for may also influence COVID-19 outbreak. For instance, vaccination coverage could significantly preclude COVID-19 outbreak, but because of limited vaccination during the study period, we could not adjust for the impact of vaccination. Future research examining the relationship between population mobility and COVID-19 infection should control for vaccination coverage in analysis.

In conclusion, within-county population mobility contributed to the geospatial disparities in county-level COVID-19 incidence in the Deep South. Population mobility has a stronger impact on COVID-19 outbreak among counties with a larger proportion of older adults. In our response to COVID-19 and other future public health emergencies, policies regarding social distancing and travel restrictions should be tailored to vulnerable communities.

Supplementary Data

Supplementary materials are available at *Clinical Infectious Diseases* online. Consisting of data provided by the authors to benefit the reader, the posted materials are not copyedited and are the sole responsibility of the authors, so questions or comments should be addressed to the corresponding author.

Notes

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