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Experienced economic segregation and associated mental health inequalities across urbanicity

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ABSTRACT

The global mental health burden is rising, with economic segregation as a key social determinant contributing to mental health and its inequalities. However, most studies rely on residential-based segregation measures failing to capture the actual segregation individuals experience through daily mobility and activities. Using a large-scale mobility dataset across the contiguous United States, we quantify mobility-based economic segregation and examine its associations with mental health outcomes across income groups and urbanicity levels. We find that individuals in the lowest and highest income quartiles exhibit strong self-segregation. A 0.1-unit increase in economic segregation is observed to be associated with a 0.64 % (95 % CI: 0.60 %–0.68 %) rise in poor mental health prevalence among lowest income quartile groups and a 0.29 % (95 % CI: 0.26 %–0.32 %) decline among highest income quartile groups in metropolitan areas. In less urbanized areas, the adverse mental health impacts of mobility-based economic segregation remain significant for low-income groups, while no significant health impact is observed for high-income groups. These findings suggest that mobility-based economic segregation may intensify economic disparities in mental health outcomes. Interventions that enhance upward social mixing for low-income individuals through changes in their mobility may help reduce adverse impacts of economic segregation on mental health and mitigate associated inequalities.

1. Introduction

Mental health is a crucial component of overall well-being, enabling individuals to manage life's stresses, perform effectively in work and learning, and contribute to society. According to the World Health Organization (WHO), by 2019, approximately 970 million people worldwide were affected by mental disorders, including anxiety and depression (World Health Organization, 2025). Furthermore, research suggests that nearly half of all individuals will experience at least one mental disorder by the age of 75 (McGrath et al., 2023). It is important to note that the absence of a mental disorder does not equate to good mental health (Silva et al., 2016). Negative mood states, if left untreated, may evolve into more serious mental health conditions. Poor mental health often leads to significant challenges in daily life, including interpersonal relationships and productivity. The rising prevalence of mental health disorders presents a major global challenge, imposing a considerable healthcare burden on society and hindering the development of healthy communities (GBD 2019 Mental Disorders Collaborators, 2022), which underscores the urgent need to address population mental health issues.

Mental health has been demonstrated to be strongly affected by social determinants, at both individual and community levels. For example, a German study indicates that individuals with lower education level tend to report worse depressive symptoms (Niemeyer et al., 2019). Mental health disorders are also linked to types of occupations and the employment conditions (Han and Lee, 2015; Stansfeld et al., 2013). Particularly, income is recognized as a crucial factors influencing residents' mental health and life satisfaction, with low-income individuals experiencing poorer mental health outcomes (Alegría et al., 2018). Moreover, people living in socioeconomically disadvantaged communities are more vulnerable to experiencing poor mental health outcomes, reflecting socioeconomic inequalities in mental health (Hong et al., 2014; Kivimäki et al., 2020). Uneven resource distribution across countries, cities, and communities, coupled with varying lifestyles among individuals from different socioeconomic backgrounds contributes to pronounced socioeconomic inequalities in mental health. Addressing these inequalities remains a crucial priority in alleviating the growing mental health burden and fostering a healthier and more

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equitable society.

Socioeconomic segregation, referring to the extent to which people with different socioeconomic backgrounds separate from each other, has been argued to be an important social determinant of health and health disparities (Carter and Zimmerman, 2022; Williams and Collins, 2001). Socioeconomic segregation systematically sorts people into different environments, e.g., neighborhoods, workplaces, and social space. It leads to unequal access to social environment and various resources, and ultimately leads to inequalities in various health outcomes (Florida and Mellander, 2018; Hardman and Ioannides, 2004; Jbaily et al., 2022; Meehan et al., 2025). Moreover, living in a segregated environment may limit opportunities to form cohesive social networks and access social capital, both of which are critical for individuals' health and well-being (Huang et al., 2020; Layte, 2012). In particular, socially disadvantaged individuals may experience greater psychosocial stress from living in segregated environments than their more affluent counterparts, contributing to chronic stress and adverse mental health outcomes (Ridley et al., 2020). In the United States, both racial and economic segregation have been a longstanding and persistent issue that leads to inequalities in health and well-being, especially in urban areas. While extensive studies have documented the adverse effects of segregation on physical health, its impact on mental health remains limited and inconclusive, especially for economic segregation (T.-C. Yang et al., 2020). For example, Lee (2009) identified an adverse effects of residential-based racial segregation on mental health among Mexican Americans. Some other studies found no significant association between racial segregation and poor mental health (Smith et al., 2022). Similarly, while several studies indicate that deprived and segregated neighborhoods are at heightened risk of adverse mental health outcomes compared to more integrated areas, other research has yielded mixed findings (Ribeiro et al., 2017; Tibber et al., 2022). Although previous segregation-mental health studies largely focused on racial segregation, some research argued that racial segregation has been decreasing since 1970s while economic segregation has been on the rise since 21st century. This trend exacerbates polarization between low- and high-income groups, which probably amplify the role of income disparities on mental health inequalities (Bor et al., 2017; Ludwig et al., 2012). As such, it is crucial to also comprehensively examine how economic segregation affect mental health inequalities, which remains insufficiently explored in the field.

Furthermore, existing studies often assess segregation based on residential location, which only reflects residents' static exposure to social environments. However, individuals typically spend most of their time outside their residential areas, with their mobility influencing where they go and whom they meet (Moro et al., 2021; Wong and Shaw, 2011). Hence, individuals' actual exposure to social environments and experienced segregation is dynamic and influenced by mobility, which differs substantially from residential segregation (Athey et al., 2021; Nilforoshan et al., 2023). For instance, individuals living in economically disadvantaged neighborhoods may experience lower levels of segregation if they spend most of their time in affluent areas and interact with higher-income individuals. Experienced segregation is crucial because it more accurately reflects real-world activities, better capturing the actual states of social interactions of residents. Thus, relying solely on residential-based approaches to assess segregation and its impact on mental health may introduce unintended research bias, e.g., underestimate the impact of socioeconomic segregation on mental health. Moreover, given the significant income disparities and urban-rural differences in mobility patterns (Alessandretti et al., 2020; Barbosa et al., 2021), it is anticipated that experienced segregation varies across income groups and urbanicity levels. Exploring these variations and their differential impacts on mental health could provide a more nuanced understanding of related mental health inequalities across income groups and urbanicity levels, which remains unexplored in existing studies.

In sum, while substantial efforts have been made, three major research gaps remain. First, existing studies have primarily focused on the impact of racial segregation on mental health, with fewer examining the role of economic segregation. Second, the measurement of segregation often relies on residential location, neglecting the actual mobility and experienced segregation, which may inaccurately estimate the association between economic segregation and mental health. Third, the nuanced associations between mental health and economic segregation across income groups and urbanicity levels remain largely unknown. To fill these gaps, drawing on over 1.2 billion aggregated mobility records at the census block group (CBG) level in the contiguous United States, this study measured mobility-based economic segregation and examined its associations with mental health outcomes across different income groups and urbanicity levels for 71,507 census tracts. Our findings provide a comprehensive understanding of mental health inequalities related to experienced economic segregation, informing policymakers implement effective social mixing strategies to develop an equitable and healthy society.

2. Methods

2.1. Study design and mental health outcome

This study was designed as a cross-sectional ecological study, focusing on contiguous United States, which consists of 48 adjoining states and the District of Columbia (excluding Alaska and Hawaii). We selected census tracts as the spatial units for the analysis, as they are the smallest statistical units for which health data is available. Census tracts are small subdivisions within a county, typically containing multiple CBGs, and generally include populations ranging from 2500 to 8000 residents. To classify the urbanicity levels for each census tract, we used the 2010 Rural-Urban Commuting Area (RUCA) Codes provided by the Economic Research Service (ERS) of the United States Department of Agriculture (USDA) (USDA, 2010). The RUCA codes define 10 primary urbanicity categories at the census tract level, based on the size and direction of primary commuting flows. To simplify our analysis, these categories were summarized into four urbanicity levels, following existing studies (Y. Yang et al., 2025). In total, 58,669 tracts were classified as metropolitan tracts, 6469 tracts were classified as micropolitan tracts, 3275 tracts were classified as small town tracts, and 3054 tracts were classified as rural tracts. A full description of the classification is provided in Supplementary Table S1.

For the mental health outcome, we obtained the crude prevalence of poor mental health from the PLACES: Local Data for Better Health project provided by the Centers for Disease Control and Prevention (CDC, 2025). We initially obtained data for 2019 to align with the timing of the mobility data. However, since data for New Jersey was missing in 2019, we thus used the data for 2018 instead in our main analysis. We did not use data for 2020 in the main analysis due to the potential confounding effects of the pandemic. The crude prevalence of poor mental health was estimated using a multilevel regression and post-stratification method, based on data from the Behavioral Risk Factor Surveillance System (BRFSS) and the American Community Survey (ACS). The BRFSS is a nationwide system of telephone surveys designed to collect health-related data from representative population samples using a rigorous sampling methodology, with over 400,000 adults participating annually. Poor mental health is measured by reporting 14 or more days of "not good" mental health in the past 30 days in the survey. Health data estimated by PLACES has been widely used in environmental health studies (Wang and Tassinary, 2024; R. Xu et al., 2023; Y. Yang et al., 2025).

2.2. Mobility data and quantifying experienced economic segregation

In this study, we used mobility data from 2019 across the contiguous United States to quantify experienced economic segregation, which was derived from SafeGraph's Weekly Patterns and Core Place datasets

(Safegraph, 2024). SafeGraph is a commercial provider who provides aggregated mobility data at the CBG level, collected from approximately 10 % of anonymous mobile phones in the United States to ensure privacy. The Weekly Patterns dataset records mobility as Origin-Destination (OD) pairs, with information including location coordinates of destination points of interest (POIs), home CBG identifiers, and the number of visitors on a weekly basis. CBGs are statistical subdivisions of census tracts, with populations ranging from 600 to 3000 individuals. Visitors' home CBGs were determined by analyzing nighttime data (6 p.m.–7 a.m.) over six weeks, with each device's location assigned at the geodash-7 level and mapped to CBGs. The SafeGraph dataset has been shown to have high representativeness, with a strong correlation between device counts and population across different spatial levels, ensuring comprehensive coverage across spatial units with varying demographic compositions (Z. Li et al., 2024). The Core Place dataset provides six-digit North American Industry Classification System (NAICS) codes to categorize each POI. We linked the Core Place dataset to the Weekly Patterns dataset using unique SafeGraph Place IDs to identify mobility records for each POI type. For computational efficiency, we selected 16 essential POI categories that meet daily recreational and residential needs, which can largely capture actual activities and social interaction of residents on both residential areas and activity sites. These categories account for over 70 % of all POIs, which ensures high representativeness for residents' activity spaces. In total, our analysis included 1,226,450,275 OD pairs across 3,227,842 POIs. Detailed information on the selected POI categories, the number of POIs and OD pairs is provided in Supplementary Table S2.

Because the mobility data are available at CBG level, we first quantified mobility-based economic segregation for each CBG and then aggregated it to the census tract level to align with the spatial resolution of mental health data. We adopted the concept of "socioeconomic distance" as the basis of measuring economic segregation, which has been widely used in social and geographical research (Abbiasov et al., 2024; X. Li et al., 2022). Socioeconomic distance refers to the perceived gap between different socioeconomic group and reflects how people with various socioeconomic backgrounds perceived their relative position compared with others. This concept provides an effective measure of segregation using continuous variables, such as income, and overcomes the loss of information inherent in many conventional measures that rely solely on categorical variables (Yao et al., 2019). To measure economic segregation, we focused on income distance, as income is strongly correlated with other economic indicators, provides a direct measure of individual and neighborhood economic status, and is a key determinant of health inequalities (Bor et al., 2017; Mitchell and Popham, 2008). Based on the concept of income distance, middle-class individuals might perceive themselves as farthest from the lowest-income individuals, while the latter might feel more distant from the highest-income individuals, but less so from the middle class. Thus, a longer income distance indicates less perceived income proximity, or greater disparity between two income groups.

To quantify the income distance between each pair of CBGs, we first ranked the CBGs according to their median household income. A naïve income distance between each pair of CBGs was calculated by their rank differences. Following Xu et al. (2019)'s approach, we used income distance to define economic dissimilarity for a given CBG_i relative to CBG_j as the proportion of CBGs whose income distance from CBG_i is smaller (smaller income rank difference) than that between CBG_i and CBG_j relative to the total number of compared CBGs.

There are two steps to quantify experienced economic segregation for the given CBG_i. First, we defined the economic dissimilarity experienced by individuals from CBG_i at a specific place n as the average economic dissimilarity between CBG_i and the home CBGs of all other individuals visiting the same place on a weekly basis, weighted by the number of visitors from different CBGs:

$$E_{(k_i,n,w)} = \frac{\sum_j V_{j,n,w} \times D_{i\rightarrow j}}{\sum_j V_{j,n,w}}$$

Where $E_{(k_i,n,w)}$ is the experienced economic dissimilarity of any individual from CBG_i at place n in a specific week w, $V_{j,n,w}$ is the number of visitors from CBG_j at the same place in the same week, and $D_{i\rightarrow j}$ is economic dissimilarity from CBG_i to CBG_j.

Second, we defined the overall experienced economic dissimilarity of CBG_i as the average experienced dissimilarity across all places throughout the whole year, weighted by the number of visitors at each place in each week:

$$E_i = \frac{\sum_w \sum_n V_{i,n,w} \times E_{(k_i,n,w)}}{\sum_w \sum_n V_{i,n,w}}$$

where $V_{i,n,w}$ is the number of visitors from CBG_i at a specific place n in week w. The mobility-based economic segregation was finally calculated as:

$$S_i = 1 - E_i$$

S_i ranges from 0 to 1, with a higher value suggesting a greater experienced economic segregation. Fig. S1 provides a conceptual framework illustrating the quantification of experienced economic segregation. The values of CBGs within the same tract were then aggregated to the corresponding tract by calculating the visitor-weighted average.

2.3. Covariates

We adjusted for potential covariates that could influence mental health outcomes. Specifically, we controlled for median household income, log-transformed population density, sex ratio, proportion of people with a lack of health insurance, and social vulnerability to account for socioeconomic and demographic factors (Gibbons et al., 2024). The socioeconomic variables were derived from the 2019 American Community Survey (ACS) 5-Year Estimates (2015–2019). Proportion of people with a lack of health insurance was obtained from the PLACE dataset. Social vulnerability indicators were obtained from the 2018 Social Vulnerability Index (SVI) reported by the Centers for Disease Control and Prevention (CDC), which includes four themes: socioeconomic status, household composition and disability, minority status and language, and housing type and transportation. We included three of these themes in the covariates, excluding socioeconomic status due to its high correlation with median household income. Additionally, we controlled for the concentration of particulate matter less than 2.5 μm (PM2.5) and greenspace exposure to account for environmental influences (Collins et al., 2020; Roberts et al., 2019; Xue et al., 2021). PM2.5 concentrations at the census tract level were derived from the CDC National Environmental Public Health Tracking Network, while greenspace exposure was measured as the population-weighted average greenspace for each census tract using the 10-m resolution European Space Agency's Global Baseline Land Cover product (Chen et al., 2022). The descriptive statistics of all variables are presented in Supplementary Table S3. Multicollinearity was assessed using the variance inflation factor (VIF). The results indicated that the VIF for all variables was below 5, suggesting that multicollinearity is minimal.

2.4. Statistical analysis

We employed multilevel linear regression models to examine the associations between mobility-based economic segregation and the prevalence of poor mental health. This approach fits the multilevel structure of our data by considering the clustering effect of poor mental health prevalence within census tracts from the same county. Specifically, census tracts (level 1) were modeled to be nested within counties (level 2), with a random effect at the county level. For ease of interpretation, we scaled the mobility-based economic segregation by a factor of ten. As a result, the coefficients can be interpreted as the change in poor mental health prevalence associated with a 0.1-unit increase in experienced economic segregation.

This study includes two sets of analyses. In the first set, we ran a main model for all census tracts to examine the overall association between mobility-based economic segregation and the prevalence of poor mental health, adjusting for socioeconomic, demographic, and environmental confounding factors. Median household income was categorized into four levels using quartiles. Additionally, we included an interaction term between income quartiles and experienced economic segregation to explore potential disparities in the associations across income groups. In the second set, we ran four distinct models for each of four urbanicity levels. Similar to the first analysis, we included an interaction term between income quartiles and experienced economic segregation in each model to investigate whether patterns of income disparities in the mental health impact of experienced economic segregation vary across urbanicity levels.

2.5. Sensitivity analysis

We also conducted sensitivity analyses to assess the robustness of our results. First, we excluded mobility within the home census tracts and focused solely on mobility occurring outside the home census tracts to quantify experienced economic segregation. We then re-performed the analysis using the experienced economic segregation outside the home census tracts. Second, we incorporated two health-related behavioral factors into the models: the proportion of people with insufficient sleep (defined as less than 7 h of sleep on average per day) and the proportion of people reporting physical inactivity in the past 30 days. These behavioral factors are potentially linked to mental health status and were included to further control for their influence. Third, we conducted additional analyses to assess the potential bias stemming from the one-year temporal misalignment between the health data and the experienced economic segregation metric. Specifically, we re-estimated the statistical models using 2019 mental health data (excluding New Jersey) and 2020 mental health data to further test the robustness of our results. It should be noted that experienced economic segregation reflects a long-term pattern shaped by persistent behavioral habits and neighborhood mobility patterns and is unlikely to change markedly over short periods. Hence, the one-year lag between the two datasets is expected to have a negligible impact on our main findings.

3. Results

3.1. Income disparities in mental health and experienced segregation by urbanicity levels

Fig. 1 presents the distribution of poor mental health prevalence across income quartiles and urbanicity levels. The Kruskal–Wallis test indicates statistically significant differences in poor mental health prevalence across income quartiles within each urbanicity level (Table S4). Post hoc analyses further reveal a statistically significant decreasing gradient, with prevalence declining from the lowest (Q1) to the highest (Q4) income quartile across all urbanicity levels. Specifically, in metropolitan tracts, the median value of prevalence was 18.1 % in the first income quartile, 15.0 % in the second, 13.2 % in the third, and 10.8 % in the fourth. In micropolitan tracts, the median was 17.7 %

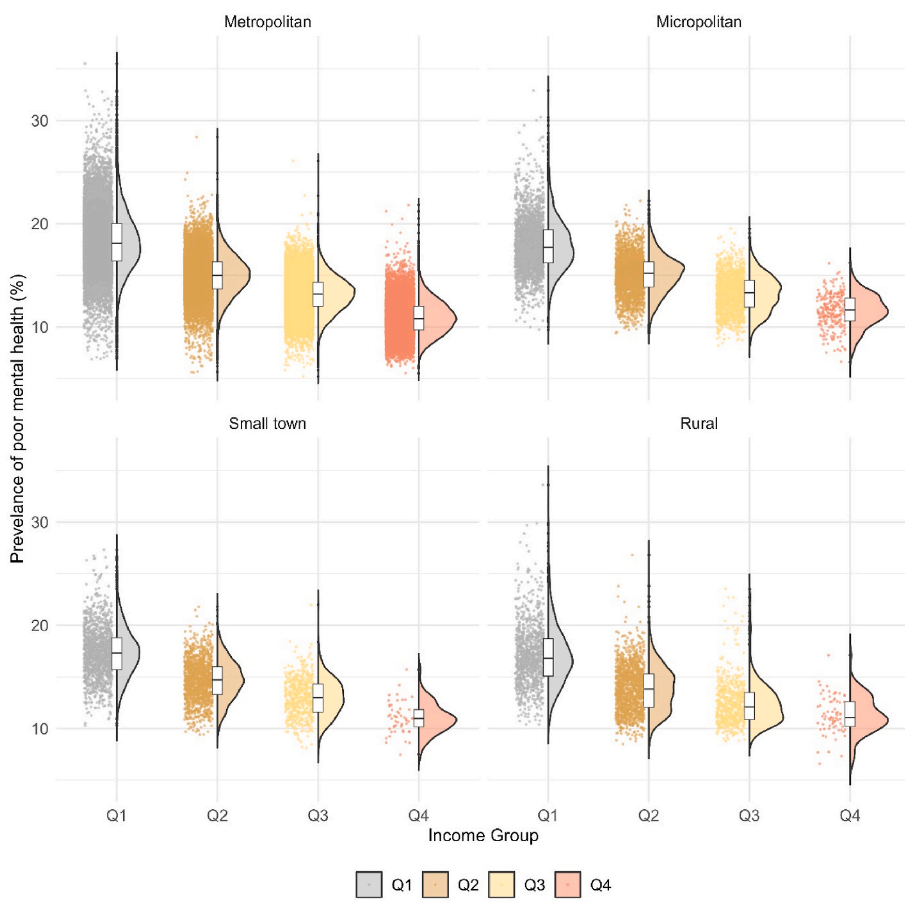

Fig. 1. Distribution of poor mental health prevalence across income groups by urbanicity levels (In each raincloud plot, the boxplot shows the data distribution, the violin plot shows the density of values, and each dot represents an individual observation, i.e., a census tract in this study).

in the first quartile, 15.2 % in the second, 13.3 % in the third, and 11.6 % in the fourth. For small towns, the median was 17.3 % in the first quartile, 14.7 % in the second, 13.0 % in the third, and 11.0 % in the fourth. Finally, in rural tracts, the median was 16.8 % in the first quartile, 13.8 % in the second, 12.1 % in the third, and 11.0 % in the fourth. These results indicate higher income people have less likelihood of having mental health issues than lower income people.

Fig. 2 presents the distribution of experienced economic segregation across income and urbanicity levels. The Kruskal-Wallis test suggests a statistically significant income disparities in experienced segregation within each urbanicity level (Table S5). The post hoc comparison shows both the lowest and highest income quartiles exhibited significant higher levels of segregation compared to the middle-income quartiles (Q2 & Q3) across all urbanicity levels, a phenomenon we refer to as "self-segregation." For example, in metropolitan areas, the median value of experienced economic segregation in the first income quartile was 0.566, which was 6.6 % higher than in the second quartile. Self-segregation was even more pronounced in the highest income quartile, with a median value of 0.671, representing increases of 18.6 %, 26.4 %, and 19.2 % compared to the first, second-, and third-income quartiles, respectively. Similarly, in micropolitan tracts, the median experienced economic segregation in the first income quartile was 0.628, which was 5.5 % and 6.6 % higher than in the second and third quartiles. The median experienced economic segregation in the fourth income quartile was 0.643, 8.1 % and 9.2 % higher than in the second and third quartiles. A similar pattern is observed in small towns, where median values for the first through fourth income quartiles were 0.651, 0.608, 0.599, and 0.653, respectively. In rural areas, the median experienced economic segregation in the first through fourth income quartiles was 0.660, 0.626, 0.625, and 0.662, respectively. Moreover, we observe that experienced economic segregation for the first, second-, and third-income quartiles decreased with increasing urbanicity level, suggesting that urbanization may promote greater social mixing among these groups. In contrast, the highest income quartiles exhibited the opposite trend, with the highest levels of experienced economic segregation occurring in metropolitan tracts. This suggests that highly urbanized cities may exacerbate self-segregation among high-income groups.

The spatial patterns of poor mental health prevalence and experienced economic segregation are presented in supplementary Figure S2 and Figure S3. Census tracts with relatively higher poor mental health prevalence are concentrated in the east-central region, which also exhibits relatively high experienced segregation. In contrast, tracts in the west north-central region show lower prevalence of poor mental health. Notably, tracts in the northeast coastal region display both relatively low poor mental health prevalence and relatively high experienced economic segregation. These patterns highlight the need to examine nuanced associations between poor mental health prevalence and experienced economic segregation.

3.2. Overall associations between experienced economic segregation and mental health

Fig. 3 visualizes the income disparities in the associations between experienced economic segregation and poor mental health prevalence. Table 1 reports the interaction term coefficients, indicating that the association for the second-, third-, and fourth-income quartiles differ significantly from that for the first quartile ($p < 0.001$). Results from the

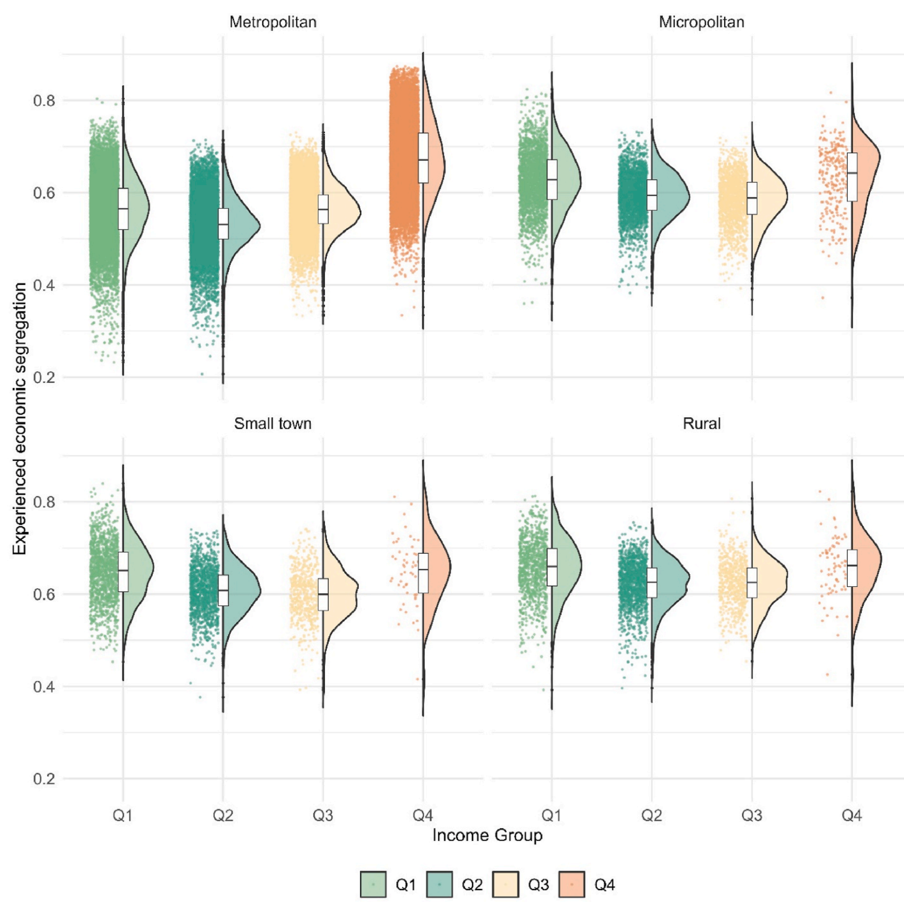

Fig. 2. Distribution of experienced economic segregation across income groups by urbanicity levels. (In each raincloud plot, the boxplot shows the data distribution, the violin plot shows the density of values, and each dot represents an individual observation, i.e., a census tract in this study).

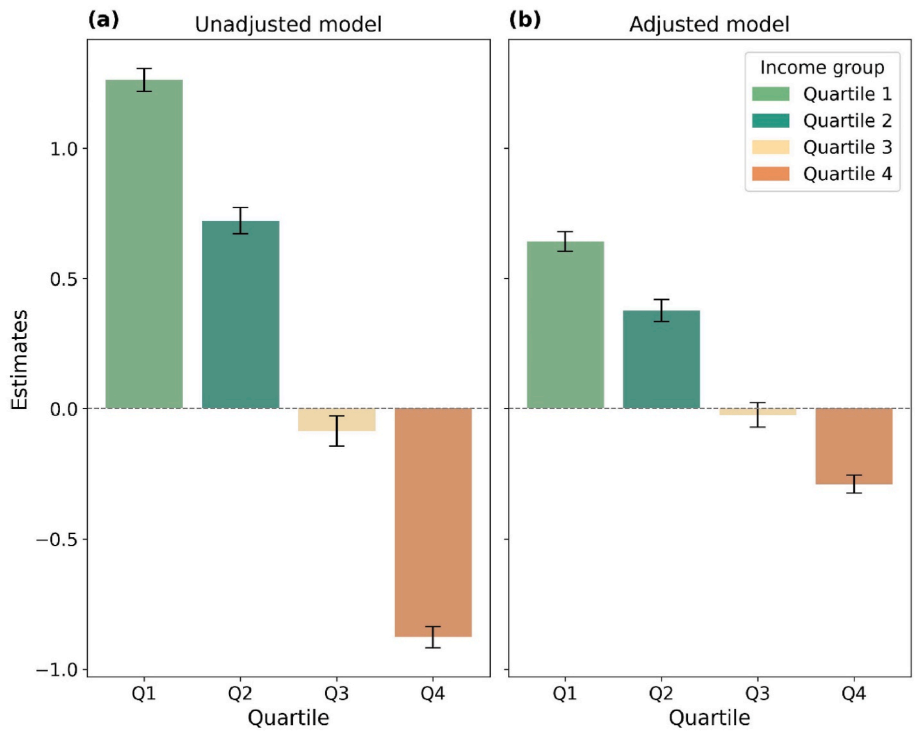

Fig. 3. Associations between mobility-based economic segregation and poor mental health prevalence across different income groups.

Table 1
Results of interaction term coefficients in the multilevel linear regression model.

	Unadjusted model		Adjusted model	
	Estimates (95 % CI)	p values	Estimates (95 % CI)	p values
Experienced economic segregation (Quartile 1)	1.26 (1.22, 1.31)	<0.001	0.64 (0.60–0.68)	<0.001
Experienced economic segregation × Quartile 2 (ref. Quartile 1)	−0.54 (−0.60, −0.48)	<0.001	−0.27 (−0.32, −0.22)	<0.001
Experienced economic segregation × Quartile 3 (ref. Quartile 1)	−1.35 (−1.42, −1.28)	0.003	−0.67 (−0.73, −0.61)	<0.001
Experienced economic segregation × Quartile 4 (ref. Quartile 1)	−2.14 (−2.20, −2.08)	<0.001	−0.93 (−0.99, −0.88)	<0.001
Control variables	No		Yes	
Marginal R2	0.60		0.60	
Conditional R2	0.76		0.86	

unadjusted model show that experienced economic segregation has adverse effects on mental health among low-income groups, while it appears to have a protective effect among high-income groups. These patterns remain consistent, although their strength is attenuated after adjusting for socioeconomic, demographic, and environmental covariates. Specifically, a 0.1-unit increase in experienced economic segregation was associated with a 0.64 % (95 % CI: 0.60 %–0.68 %) and 0.38 % (95 % CI: 0.33 %–0.42 %) increase in poor mental health prevalence in the first- and second-income quartiles, respectively. In contrast, a 0.1-unit increase in experienced economic segregation was associated with a 0.29 % (95 % CI: 0.26 %–0.32 %) decrease in poor mental health prevalence in the highest income quartile. No statistically significant association is observed for the third income quartile.

3.3. *Disparate associations across urbanicity level*

In the second set of analysis, we ran four separated models with data stratified by urbanicity levels. Fig. 4 shows the income disparity in the associations between experienced economic segregation and poor mental health prevalence across four urbanicity levels. The overall pattern is consistent between the unadjusted and covariate-adjusted models, although the strength of the associations is attenuated in the adjusted models. In metropolitan areas, we observe a reverse pattern in

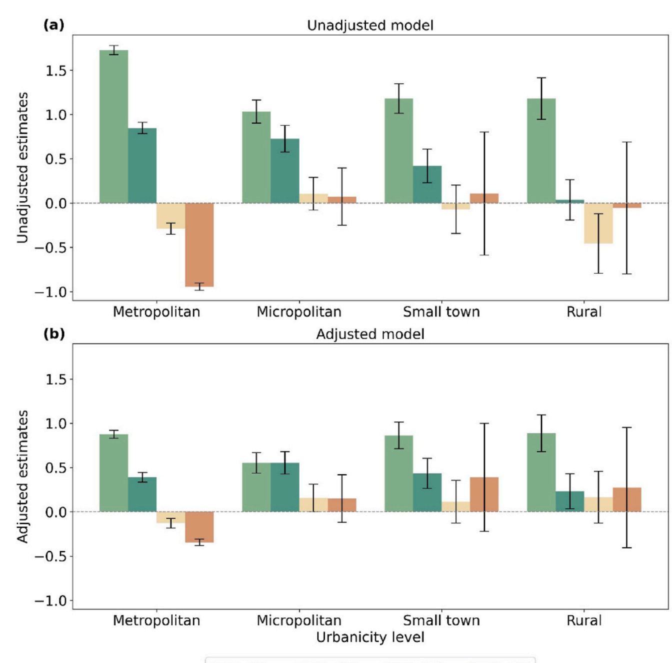

Fig. 4. Income disparities in associations between mobility-based economic segregation and poor mental health prevalence across urbanicity levels.

the mental health impacts of experienced economic segregation between low-income and high-income groups. Specifically, after adjusting for socioeconomic, demographic, and environmental factors, a 0.1-unit increase in experienced economic segregation was associated with a 0.88 % (95 % CI: 0.83 %–0.92 %) and 0.39 % (95 % CI: 0.34 %–0.44 %) increase in poor mental health prevalence in the first- and second-income quartiles, respectively. In contrast, a 0.1-unit increase in experienced economic segregation was associated with a 0.13 % (95 % CI: 0.07 %–0.18 %) and 0.35 % (95 % CI: 0.31 %–0.38 %) decline in poor mental health prevalence in the third- and fourth-income quartiles. Moreover, the adverse impact of experienced economic segregation on mental health in the lowest income quartile was significantly greater than that in the second income quartile, while the protective health impact in the highest income quartile was significantly greater than that in the third quartile.

In less urbanized areas, namely micropolitan tracts, small towns, and rural tracts, we also observe adverse impacts of experienced economic segregation on mental health in the first- and second-income quartile groups. Specifically, in micropolitan tracts, a 0.1-unit increase in experienced economic segregation was associated with a 0.55 % (95 % CI: 0.44 %–0.68 %) and 0.55 % (95 % CI: 0.43 %–0.68 %) increase in poor mental health prevalence in the first- and second-income quartiles, respectively. In small towns, the figures were 0.86 % (95 % CI: 0.71 %–1.01 %) and 0.43 % (95 % CI: 0.26 %–0.60 %) for the first- and second-income quartiles, while in rural tracts, the figures were 0.88 % (95 % CI: 0.68 %–1.10 %) and 0.23 % (95 % CI: 0.03 %–0.43 %) for the first- and second-income quartiles. However, no statistically significant associations are observed in the higher income quartile groups (Q3 & Q4) in these areas.

3.4. Sensitivity analysis

For the first sensitivity analysis, we used outside-home-tract experienced economic segregation as the exposure variable. The results of the full sample model remain consistent with our primary findings, showing a positive association between experienced economic segregation and poor mental health prevalence in lower-income quartile groups and a negative association in higher-income quartile groups (Fig. S4). Moreover, the stratified models confirm that the patterns across different urbanicity levels aligned with our primary results. Specifically, adverse impacts of experienced economic segregation on mental health are observed in the first- and second-income quartile groups across all urbanicity levels. In contrast, protective effects of experienced economic segregation on mental health are observed only in metropolitan tracts in the third- and fourth-income quartile groups, with no clear effects in these income groups in less urbanized areas (Fig. S5).

For the second sensitivity analysis, we additionally controlled for two health-related behavioral factors in the models. The income disparities in the associations between experienced economic segregation and poor mental health prevalence remain consistent with our primary analyses, although no statistically significant difference is found in the adverse impacts between the first- and second-income quartile groups (Fig. S6). In terms of patterns across urbanicity levels, the reverse impacts of experienced economic segregation on the lower- and higher-income quartile groups remain consistent with our main findings. In less urbanized areas, a positive association between experienced economic segregation and poor mental health prevalence is observed only in the second income quartile group in micropolitan tracts and in the first income quartile group in small towns, with no statistically significant associations observed for the other income quartile groups in these areas (Fig. S7). Overall, the results of the sensitivity analyses remain largely consistent with our primary analyses, further supporting the robustness of our findings.

For the third and fourth sensitivity analyses, we used 2019 mental health data excluding New Jersey and 2020 mental health data as outcome variables, respectively. Although the strength of the associations differs slightly, the overall pattern of disparities across income groups and urbanicity levels remain consistent with the main findings (Fig. S8–S11). These results indicate that the one-year lag between health and mobility data has a negligible impact on the analysis of segregation–mental health relationships and confirm the robustness of our findings.

4. Discussion

Social determinants of mental health have been extensively studied, with segregation recognized as a driver of health inequalities. Several studies have linked socioeconomic segregation to mental health outcomes, yet findings remain inconsistent, which is partly due to different measurements of segregation. Traditional studies primarily rely on residential-based segregation measures, which overlook the spatial dynamics of individuals' daily activities and fail to capture the actual experienced socioeconomic segregation, closely tied to mental health status. Furthermore, little evidence is available on the link between economic segregation and mental health outcomes. Given the context of growing global mental health burden and rising economic segregation, it is necessary to investigate the link between mobility-based economic segregation and mental health outcome. To address this gap, we leverage large-scale human mobility data to quantify mobility-based economic segregation across the contiguous United States and assess its association with poor mental health prevalence across income groups and urbanicity levels. To the best of our knowledge, this is the first attempt to conduct a nationwide study to examine the association between mental health and experienced economic segregation using a mobility-based framework. Our findings reveal pronounced income disparities in these associations across different urbanicity levels, which further extends previous studies that have primarily focused on urban areas and overlooked income-stratified effects. Our analyses underscore the importance of integrating human mobility into measuring experienced economic segregation and unveil its associations with mental health inequalities.

4.1. Principal findings

Our findings show inherent income inequalities in poor mental health prevalence in the United States, with higher income census tracts exhibiting lower prevalence of poor mental health. These inequalities are particularly pronounced in highly urbanized areas, namely, metropolitan tracts, where the average prevalence in the lowest-income quartile is over 40 % higher than that in the highest-income quartile. These findings are aligned with existing studies, suggesting that low-income individuals are more vulnerable to poor mental health conditions, e.g., depression, anxiety, self-harm, and suicide attempts (Iemmi et al., 2016; Ridley et al., 2020; Silva et al., 2016; Stack, 2021). Such health inequalities may intensify in the context of rising income inequality (Bor et al., 2017). Low-income individuals often experience lower job satisfaction, limited educational attainment, and substandard housing conditions, all of which contribute to heightened life stress and an increased likelihood of poor mental health outcomes (Patel et al., 2018; Ridley et al., 2020).

Furthermore, we observe that individuals from tracts with the lowest income quartile and highest income quartiles tend to experience higher levels of mobility-based economic segregation compared to those from tracts with middle income quartiles. These findings are consistent with prior studies suggesting that people with similar socioeconomic background tend to interact with each other, especially among high-income people, who often frequent amenities with financial barriers, such as golf courses and high-end shopping malls (Reardon and Bischoff, 2011). Moreover, our analysis reveals that highly urbanized cities may further reinforce this self-segregation among high-income individuals.

Our findings reveal a noticeable income disparity on the association between experienced economic segregation and mental health. Specifically, experienced economic segregation is positively associated with poor mental health prevalence among individuals from lower-income census tracts, whereas it exhibits a negative association among those from higher-income census tracts. Our results confirm that experienced economic segregation adversely affects mental health among low-income groups, aligning with studies focusing on residential segregation suggesting that concentrated poverty and segregation among disadvantaged populations are detrimental to health (Ribeiro et al., 2017; T.-C. Yang et al., 2020). Importantly, we show that segregation among high-income groups is associated with lower prevalence of mental health issues—an underexplored finding in prior research. These income disparities highlight the importance of distinguishing the mental health influence of segregation across income groups, rather than assuming a uniform effect. These findings suggest that experienced economic segregation exacerbates income inequalities in mental health outcomes, confirming the notion that segregation serves as a fundamental driver of mental health inequalities (Williams and Collins, 2001).

We provide two possible interpretations for the opposite mental health impacts of experienced economic segregation. First, individuals from lower-income communities inherently experience poorer living conditions (Kirkpatrick and Tarasuk, 2011; Meehan et al., 2025), greater environmental hazards (Jbaily et al., 2022; Kodros et al., 2022), heightened safety concerns (Jackson et al., 2009; Pino et al., 2023), and reduced social capital (Patel et al., 2018) in their neighborhoods compared to those in more affluent areas, all of which negatively affect their well-being. Low-income segregation may further reinforce these disadvantages, as low-income individuals whose activities are largely confined to deprived neighborhoods may become entrenched in unsatisfied and unhealthy environments, ultimately diminishing life satisfaction and well-being. Conversely, individuals from higher-income communities have greater access to resources that support a high quality of life, including better job opportunities, healthier food environments, and a wider range of recreational resources and leisure activities (K. F. Anderson and Galaskiewicz, 2021; Moore et al., 2008; Moro et al., 2021; Rigolon et al., 2018). When they primarily occupy spaces with financial barriers and engage in these activities, high-income segregation may be reinforced, amplifying the positive effects of these advantages on well-being. Second, social interaction with people with different socioeconomic backgrounds shapes individual's behavior and access to information. For example, studies suggest that low-income segregation is associated with unhealthy behaviors (Larson et al., 2009; Rose et al., 2024). Additionally, low-income people are more vulnerable to low-quality and depressive information (Hamilton and Morgan, 2018). When their social interactions are largely confined to others with similarly deprived status, they may experience persistent passivity and pessimism resulting from negative information, thereby negatively affecting well-being. However, among affluent individuals who primarily interact with others of similar socioeconomic backgrounds, positive feedback mechanisms may emerge. The concentration of beneficial and positive information within these social networks can promote healthier lifestyles and life satisfaction, reducing the probability of poor mental health outcomes.

Our findings further reveal that the adverse effects of experienced economic segregation on poor mental health prevalence among low-income individuals remain consistent across different levels of urbanicity, whereas the protective effects among high-income individuals are evident only in highly urbanized areas, i.e., metropolitan regions. This is probably due to increasing economic segregation in large cities (Nilforoshan et al., 2023). Highly urbanized cities reinforce the social networks of high-income communities and provide more social opportunities and options for high-income individuals, enabling them to benefit more readily from concentrated resources and, consequently, achieve better mental well-being. In addition, the adverse mental health effects of mobility-based economic segregation among low-income individuals persist regardless of urbanicity levels. This highlights the universal disadvantages of low-income segregation on well-being and mental health.

4.2. Implications

Overall, our study highlights we may effectively mitigate socioeconomic inequalities in mental health outcomes by reducing experienced income segregations among lower-income residents, particularly in highly urbanized cities. While previous studies have advocated for local interventions such as mixed-income housing and the development of public recreational spaces to reduce residential segregation (L. M. Anderson et al., 2003; Peters, 2010), their impact on mobility-based segregation remains limited. Beyond residential segregation, our findings suggest that activity patterns and mobility-based segregation may further exacerbate income inequalities in mental health. Thus, fostering economic upward mobility and social mixing for individuals from low-income communities is crucial to reducing their exposure to economic segregation and mitigating its negative effects on mental health. This is especially important in large cities. As urbanization progresses, high-income individuals increasingly concentrate resources, leveraging social networks to access economic opportunities and enhance well-being, thereby exacerbating income disparities, especially in mental health. To counterbalance these inequalities, enhancing experienced social mixing through mobility-based interventions is essential for low-income individuals to obtain social capital and resources, thereby promoting their well-being. For example, developing well-connected and affordable public transit systems in cities can serve as a promising strategy to facilitate economic upward mobility (Barbosa et al., 2021; Iyer et al., 2024). Improved public transportation may increase the travel diversity of low-income residents and enable their movement beyond less affluent neighborhoods, thereby broadening access to amenities and enhancing social mixing. In addition, increasing job accessibility and economic opportunities for low-income residents can help them develop diverse social networks. This not only effectively improves their earnings and maintains financial stability, thereby reducing their life stress, but also helps them get rid of negative information prevalence in low-income segregation, ultimately enhancing life satisfaction.

4.3. Limitations

This study has several limitations. First, while individual mobility patterns vary throughout the day, the mobility data used in this study is aggregated on a weekly basis due to privacy protections. As a result, we are unable to capture daily variations in activities within the same week. Instead, we captured the co-location patterns for individuals from different neighborhoods and their experienced economic dissimilarity with others, reflecting a general tendency of neighborhood mobility patterns. Moreover, it is important to note that we utilized mobility data spanning the entire year of 2019, which we believe captures general mobility patterns and tendencies across different neighborhoods, thereby mitigating potential biases associated with weekly-based aggregated data. Similarly, because the mobility data is aggregated at the census tract level, this study was conducted as an ecological analysis. Future research should consider individual-level studies to provide more robust evidence if relevant mobility data becomes available. Second, mental health encompasses multiple dimensions, including anxiety, depression, and stress. Due to data limitations, this study focuses on poor mental health outcomes as a broad indicator. Nevertheless, our findings reveal a general pattern of income inequalities in mental health associated with mobility-based economic segregation, offering valuable insights to advance the field. Future research should examine the mental health effects of mobility-based segregation across different dimensions to gain a more comprehensive understanding. Third, our study establishes correlation relationships between mobility-based economic segregation and mental health outcomes, while causal relationships remain unexplored. The findings should be interpreted with caution, and future studies should seek to establish causal links using panel dataset to better understand the long-term mental health impacts of mobility-based economic segregation.

5. Conclusion

In conclusion, drawing on a large-scale mobility dataset, we conducted a nationwide study to quantify mobility-based economic segregation and examine its associations with mental health outcomes across different income groups and urbanicity levels. Our findings suggest that experienced economic segregation in highly urbanized areas exacerbates mental health inequalities between low- and high-income groups. Mobility-based interventions are recommended to facilitate upward social mixing among individuals from low-income communities, thereby improving their mental health and well-being. This study provides valuable insights for addressing mental health inequalities and mitigating the growing mental health burden, especially in urban areas.

CRediT authorship contribution statement

Yuxuan Zhou: Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Conceptualization. **Yi Lu:** Writing – review & editing, Supervision, Resources, Data curation.

Ethics approval/statement EA not required

This study used aggregated mobility data from SafeGraph, which is commercially available and can be requested for research purposes (https://www.safegraph.com/pricing). Health data were sourced from PLACES: Local Data for Better Health project provided by the Centers for Disease Control and Prevention (https://www.cdc.gov/places/index.html). As both datasets contain no individual-level information, ethics approval was not required for this study.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.socscimed.2025.118813.

Data availability

The authors do not have permission to share data.

References

Abbiasov, T., Heine, C., Sabouri, S., Salazar-Miranda, A., Santi, P., Glaeser, E., Ratti, C., 2024. The 15-minute city quantified using human mobility data. Nat. Hum. Behav. 1–11. https://doi.org/10.1038/s41562-023-01770-y.

Alegría, M., NeMoyer, A., Falgàs Bagué, I., Wang, Y., Alvarez, K., 2018. Social determinants of mental health: where we are and where we need to Go. Curr. Psychiatry Rep. 20 (11), 95. https://doi.org/10.1007/s11920-018-0969-9.

Alessandretti, L., Aslak, U., Lehmann, S., 2020. The scales of human mobility. Nature 587 (7834). https://doi.org/10.1038/s41586-020-2909-1. Article 7834.

Anderson, K.F., Galaskiewicz, J., 2021. Racial/Ethnic residential segregation, socioeconomic inequality, and job accessibility by public transportation networks in the United States. Spatial Demography 9 (3), 341–373. https://doi.org/10.1007/s40980-021-00093-8.

Anderson, L.M., St Charles, J., Fullilove, M.T., Scrimshaw, S.C., Fielding, J.E., Normand, J., 2003. Providing affordable family housing and reducing residential segregation by income: a systematic review. Am. J. Prev. Med. 24 (3, Suppl. ment), 47–67. https://doi.org/10.1016/S0749-3797(02)00656-6.

Athey, S., Ferguson, B., Gentzkow, M., Schmidt, T., 2021. Estimating experienced racial segregation in US cities using large-scale GPS data. Proc. Natl. Acad. Sci. 118 (46), e2026160118. https://doi.org/10.1073/pnas.2026160118.

Barbosa, H., Hazarie, S., Dickinson, B., Bassolas, A., Frank, A., Kautz, H., Sadilek, A., Ramasco, J.J., Ghoshal, G., 2021. Uncovering the socioeconomic facets of human mobility. Sci. Rep. 11 (1), 8616. https://doi.org/10.1038/s41598-021-87407-4.

Bor, J., Cohen, G.H., Galea, S., 2017. Population health in an era of rising income inequality: USA, 1980–2015. Lancet 389 (10077), 1475–1490. https://doi.org/10.1016/S0140-6736(17)30571-8.

Carter, P.M., Zimmerman, M.A., 2022. Addressing residential segregation as a social determinant of health. JAMA Netw. Open 5 (6), e2222619. https://doi.org/10.1001/jamanetworkopen.2022.22619.

CDC, 2025. *Health Outcomes*. PLACES: local data for better health. https://www.cdc.gov/places/measure-definitions/health-outcomes.html.

Chen, B., Wu, S., Song, Y., Webster, C., Xu, B., Gong, P., 2022. Contrasting inequality in human exposure to greenspace between cities of global north and global south. Nat. Commun. 13 (1). https://doi.org/10.1038/s41467-022-32258-4. Article 1.

Collins, R.M., Spake, R., Brown, K.A., Ogutu, B.O., Smith, D., Eigenbrod, F., 2020. A systematic map of research exploring the effect of greenspace on mental health. Landsc. Urban Plann. 201, 103823. https://doi.org/10.1016/j.landurbplan.2020.103823.

Florida, R., Mellander, C., 2018. The geography of economic segregation. Soc. Sci. 7 (8). https://doi.org/10.3390/socsci7080123. Article 8.

GBD 2019 Mental Disorders Collaborators, 2022. Global, regional, and national burden of 12 mental disorders in 204 countries and territories, 1990–2019: a systematic analysis for the global burden of disease study 2019. Lancet Psychiatry 9 (2), 137–150. https://doi.org/10.1016/S2215-0366(21)00395-3.

Gibbons, R.D., Olfson, M., Saulsberry, L., Edlund, M.J., Zangeneh, S., Bareis, N., Chwastiak, L., Gibbons, J.B., Kessler, R.C., 2024. Social vulnerability and prevalence and treatment for mental health and substance use disorders. JAMA Psychiatry 81 (10), 976–984. https://doi.org/10.1001/jamapsychiatry.2024.1870.

Hamilton, J.T., Morgan, F., 2018. Poor information: how economics affects the information lives of low-income individuals. Int. J. Commun. 12 (0). Article 0. https://ijoc.org/index.php/ijoc/article/view/8340.

Han, S., Lee, H.-S., 2015. Social capital and depression: does household context matter? Asia Pac. J. Publ. Health 27 (2), NP2008–NP2018. https://doi.org/10.1177/1010539513496140.

Hardman, A., Ioannides, Y.M., 2004. Neighbors' income distribution: economic segregation and mixing in US urban neighborhoods. J. Hous. Econ. 13 (4), 368–382. https://doi.org/10.1016/j.jhe.2004.09.003.

Hong, S., Zhang, W., Walton, E., 2014. Neighborhoods and mental health: exploring ethnic density, poverty, and social cohesion among Asian Americans and Latinos. Soc. Sci. Med. 111, 117–124. https://doi.org/10.1016/j.socscimed.2014.04.014.

Huang, Y., Edwards, J., Laurel-Wilson, M., 2020. The shadow of context: neighborhood and school socioeconomic disadvantage, perceived social integration, and the mental and behavioral health of adolescents. Health Place 66, 102425. https://doi.org/10.1016/j.healthplace.2020.102425.

Iemmi, V., Bantjes, J., Coast, E., Channer, K., Leone, T., McDaid, D., Palfreyman, A., Stephens, B., Lund, C., 2016. Suicide and poverty in low-income and middle-income countries: a systematic review. Lancet Psychiatry 3 (8), 774–783. https://doi.org/10.1016/S2215-0366(16)30066-9.

Iyer, N., Menezes, R., Barbosa, H., 2024. Mobility and transit segregation in urban spaces. Environ. Plan. B Urban Anal. City Sci. 51 (7), 1496–1512. https://doi.org/10.1177/23998083231219294.

Jackson, L., Langille, L., Lyons, R., Hughes, J., Martin, D., Winstanley, V., 2009. Does moving from a high-poverty to lower-poverty neighborhood improve mental health? A realist review of 'Moving to Opportunity'. Health Place 15 (4), 961–970. https://doi.org/10.1016/j.healthplace.2009.03.003.

Jbaily, A., Zhou, X., Liu, J., Lee, T.-H., Kamareddine, L., Verguet, S., Dominici, F., 2022. Air pollution exposure disparities across US population and income groups. Nature 601 (7892), 228–233. https://doi.org/10.1038/s41586-021-04190-y.

Kirkpatrick, S.I., Tarasuk, V., 2011. Housing circumstances are associated with household food access among low-income urban families. J. Urban Health 88 (2), 284–296. https://doi.org/10.1007/s11524-010-9535-4.

Kivimäki, M., Batty, G.D., Pentti, J., Shipley, M.J., Sipilä, P.N., Nyberg, S.T., Suominen, S.B., Oksanen, T., Stenholm, S., Virtanen, M., Marmot, M.G., Singh-Manoux, A., Brunner, E.J., Lindbohm, J.V., Ferrie, J.E., Vahtera, J., 2020. Association between socioeconomic status and the development of mental and physical health conditions in adulthood: a multi-cohort study. Lancet Public Health 5 (3), e140–e149. https://doi.org/10.1016/S2468-2667(19)30248-8.

Kodros, J.K., Bell, M.L., Dominici, F., L'Orange, C., Godri Pollitt, K.J., Weichenthal, S., Wu, X., Volckens, J., 2022. Unequal airborne exposure to toxic metals associated with race, ethnicity, and segregation in the USA. Nat. Commun. 13 (1), 6329. https://doi.org/10.1038/s41467-022-33372-z.

Larson, N.I., Story, M.T., Nelson, M.C., 2009. Neighborhood environments: disparities in access to healthy foods in the U.S. Am. J. Prev. Med. 36 (1), 74–81.e10. https://doi.org/10.1016/j.amepre.2008.09.025.

Layte, R., 2012. The association between income inequality and mental health: testing status anxiety, social capital, and neo-materialist explanations. Eur. Socio Rev. 28 (4), 498–511. https://doi.org/10.1093/esr/jcr012.

Lee, M.-A., 2009. Neighborhood residential segregation and mental health: a multilevel analysis on Hispanic Americans in Chicago. Soc. Sci. Med. 68 (11), 1975–1984. https://doi.org/10.1016/j.socscimed.2009.02.040.

Li, X., Huang, X., Li, D., Xu, Y., 2022. Aggravated social segregation during the COVID-19 pandemic: evidence from crowdsourced mobility data in twelve most populated U.S. metropolitan areas. Sustain. Cities Soc. 81, 103869. https://doi.org/10.1016/j.scs.2022.103869.

Li, Z., Ning, H., Jing, F., Lessani, M.N., 2024. Understanding the bias of mobile location data across spatial scales and over time: a comprehensive analysis of SafeGraph data in the United States. PLoS One 19 (1), e0294430. https://doi.org/10.1371/journal.pone.0294430.

Ludwig, J., Duncan, G.J., Gennetian, L.A., Katz, L.F., Kessler, R.C., Kling, J.R., Sanbonmatsu, L., 2012. Neighborhood effects on the long-term well-being of low-income adults. Science 337 (6101), 1505–1510. https://doi.org/10.1126/science.1224648.

McGrath, J.J., Al-Hamzawi, A., Alonso, J., Altwaijri, Y., Andrade, L.H., Bromet, E.J., Bruffaerts, R., de Almeida, J.M.C., Chardoul, S., Chiu, W.T., Degenhardt, L., Demler, O.V., Ferry, F., Gureje, O., Haro, J.M., Karam, E.G., Karam, G., Khaled, S.M., Kovess-Masfety, V., et al., 2023. Age of onset and cumulative risk of mental disorders: a cross-national analysis of population surveys from 29 countries. Lancet Psychiatry 10 (9), 668–681. https://doi.org/10.1016/S2215-0366(23)00193-1.

Meehan, K., Jurjevich, J.R., Everitt, L., Chun, N.M.J.W., Sherrill, J., 2025. Urban inequality, the housing crisis and deteriorating water access in US cities. Nature Cities 2 (1), 93–103. https://doi.org/10.1038/s44284-024-00180-z.

Mitchell, R., Popham, F., 2008. Effect of exposure to natural environment on health inequalities: an observational population study. Lancet 372 (9650), 1655–1660. https://doi.org/10.1016/S0140-6736(08)61689-X.

Moore, L.V., Diez Roux, A.V., Evenson, K.R., McGinn, A.P., Brines, S.J., 2008. Availability of recreational resources in minority and low socioeconomic status areas. Am. J. Prev. Med. 34 (1), 16–22. https://doi.org/10.1016/j.amepre.2007.09.021.

Moro, E., Calacci, D., Dong, X., Pentland, A., 2021. Mobility patterns are associated with experienced income segregation in large US cities. Nat. Commun. 12 (1). https://doi.org/10.1038/s41467-021-24899-8. Article 1.

Niemeyer, H., Bieda, A., Michalak, J., Schneider, S., Margraf, J., 2019. Education and mental health: do psychosocial resources matter? SSM - Population Health 7, 100392. https://doi.org/10.1016/j.ssmph.2019.100392.

Nilforoshan, H., Looi, W., Pierson, E., Villanueva, B., Fishman, N., Chen, Y., Sholar, J., Redbird, B., Grusky, D., Leskovec, J., 2023. Human mobility networks reveal increased segregation in large cities. Nature 1–7. https://doi.org/10.1038/s41586-023-06757-3.

Patel, V., Burns, J.K., Dhingra, M., Tarver, L., Kohrt, B.A., Lund, C., 2018. Income inequality and depression: a systematic review and meta-analysis of the association and a scoping review of mechanisms. World Psychiatry 17 (1), 76–89. https://doi.org/10.1002/wps.20492.

Peters, K., 2010. Being together in urban parks: connecting public space, leisure, and diversity. Leisure Sci. 32 (5), 418–433. https://doi.org/10.1080/01490400.2010.510987.

Pino, E.C., Jacoby, S.F., Dugan, E., Jay, J., 2023. Exposure to neighborhood racialized economic segregation and reinjury and violence perpetration among survivors of violent injuries. JAMA Netw. Open 6 (4), e238404. https://doi.org/10.1001/jamanetworkopen.2023.8404.

Reardon, S.F., Bischoff, K., 2011. Income inequality and income segregation. Am. J. Sociol. 116 (4), 1092–1153. https://doi.org/10.1086/657114.

Ribeiro, W.S., Bauer, A., Andrade, M.C.R., York-Smith, M., Pan, P.M., Pingani, L., Knapp, M., Coutinho, E.S.F., Evans-Lacko, S., 2017. Income inequality and mental illness-related morbidity and resilience: a systematic review and meta-analysis. Lancet Psychiatry 4 (7), 554–562. https://doi.org/10.1016/S2215-0366(17)30159-1.

Ridley, M., Rao, G., Schilbach, F., Patel, V., 2020. Poverty, depression, and anxiety: causal evidence and mechanisms. Science 370 (6522). https://doi.org/10.1126/science.aay0214 eaay0214.

Rigolon, A., Browning, M., Jennings, V., 2018. Inequities in the quality of urban park systems: an environmental justice investigation of cities in the United States. Landsc. Urban Plann. 178, 156–169. https://doi.org/10.1016/j.landurbplan.2018.05.026.

Roberts, S., Arseneault, L., Barratt, B., Beevers, S., Danese, A., Odgers, C.L., Moffitt, T.E., Reuben, A., Kelly, F.J., Fisher, H.L., 2019. Exploration of NO2 and PM2.5 air pollution and mental health problems using high-resolution data in London-based children from a UK longitudinal cohort study. Psychiatry Res. 272, 8–17. https://doi.org/10.1016/j.psychres.2018.12.050.

Rose, S.W., Rayens, M.K., Azadi, M., Kierstead, E.C., Kong, A.Y., Horn, K., 2024. Examining the relationship between racial, ethnic, and economic residential segregation and cigarette smoking among a nationally representative sample of young adults. Nicotine Tob. Res. https://doi.org/10.1093/ntr/ntae277 ntae277.

Safegraph, 2024. Places data curated for accurate geospatial analytics | SafeGraph. https://safegraph.com/.

Silva, M., Loureiro, A., Cardoso, G., 2016. Social determinants of mental health: a review of the evidence. Eur. J. Psychiatr. 30 (4), 259–292. https://scielo.isciii.es/scielo.php?script=sci_abstract&pid=S0213-61632016000400004&lng=es&nrm=iso&tlng=en.

Smith, R.J., Baik, S., Lehning, A.J., Mattocks, N., Cheon, J.H., Kim, K., 2022. Residential segregation, social cohesion, and aging in place: health and mental health inequities. Gerontol. 62 (9), 1289–1298. https://doi.org/10.1093/geront/gnac076.

Stack, S., 2021. Contributing factors to suicide: political, social, cultural and economic. Prev. Med. 152, 106498. https://doi.org/10.1016/j.ypmed.2021.106498.

Stansfeld, S.A., Pike, C., McManus, S., Harris, J., Bebbington, P., Brugha, T., Hassiotis, A., Jenkins, R., Meltzer, H., Moran, P., Clark, C., 2013. Occupations, work characteristics and common mental disorder. Psychol. Med. 43 (5), 961–973. https://doi.org/10.1017/S0033291712001821.

Tibber, M.S., Walji, F., Kirkbride, J.B., Huddy, V., 2022. The association between income inequality and adult mental health at the subnational level—A systematic review. Soc. Psychiatr. Psychiatr. Epidemiol. 57 (1), 1–24. https://doi.org/10.1007/s00127-021-02159-w.

USDA, 2010. 2010 rural-urban commuting area (RUCA) codes. https://www.ers.usda.gov/data-products/rural-urban-commuting-area-codes/documentation/.

Wang, H., Tassinary, L.G., 2024. Association between greenspace morphology and prevalence of non-communicable diseases mediated by air pollution and physical activity. Landsc. Urban Plann. 242, 104934. https://doi.org/10.1016/j.landurbplan.2023.104934.

Williams, D.R., Collins, C., 2001. Racial residential segregation: a fundamental cause of racial disparities in health. Public Health Reports® 116 (5), 404–416. https://doi.org/10.1093/phr/116.5.404.

Wong, D.W.S., Shaw, S.-L., 2011. Measuring segregation: an activity space approach. J. Geogr. Syst. 13 (2), 127–145. https://doi.org/10.1007/s10109-010-0112-x.

World Health Organization, 2025. Mental health. https://www.who.int/health-topics/mental-health.

Xu, R., Huang, X., Zhang, K., Lyu, W., Ghosh, D., Li, Z., Chen, X., 2023. Integrating human activity into food environments can better predict cardiometabolic diseases in the United States. Nat. Commun. 14 (1). https://doi.org/10.1038/s41467-023-42667-8. Article 1.

Xu, Y., Belyi, A., Santi, P., Ratti, C., 2019. Quantifying segregation in an integrated urban physical-social space. J. R. Soc. Interface 16 (160), 20190536. https://doi.org/10.1098/rsif.2019.0536.

Xue, T., Guan, T., Zheng, Y., Geng, G., Zhang, Q., Yao, Y., Zhu, T., 2021. Long-term PM2.5 exposure and depressive symptoms in China: a quasi-experimental study. The Lancet Regional Health – Western Pacific 6. https://doi.org/10.1016/j.lanwpc.2020.100079.

Yang, T.-C., Park, K., Matthews, S.A., 2020. Racial/ethnic segregation and health disparities: future directions and opportunities. Sociology Compass 14 (6), e12794. https://doi.org/10.1111/soc4.12794.

Yang, Y., Jiang, B., Wang, L., Zhou, Y., Li, B., Gong, P., 2025. Thinking beyond general greenness: the nuanced associations between a variety of greenspaces and cardiovascular diseases across urbanicity. Landsc. Urban Plann. 253, 105223. https://doi.org/10.1016/j.landurbplan.2024.105223.

Yao, J., Wong, D.W.S., Bailey, N., Minton, J., 2019. Spatial segregation measures: a methodological review. Tijdschr. Econ. Soc. Geogr. 110 (3), 235–250. https://doi.org/10.1111/tesg.12305.