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While Some Things Change, Do Others Stay the Same? The Heterogeneity of Neighborhood Health Returns to Gentrification

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Abstract

Gentrification is associated with decreases in neighborhood poverty and crime, increases in amenities and services, among other benefits—all identified as structural determinants of health. However, gentrification is also associated with population-level replacement of the existing community, or threats thereof. Combining census data from the ten largest MSAs in the U.S. with tract-level estimates from the CDC-PLACES Project from 2013–14 to 2017–18, we explore how the changing socioeconomic conditions in gentrifying neighborhoods correlate with changes in neighborhood health. We find significant differences between gentrifying and non-gentrifying neighborhoods in their associations with neighborhood health. The sociodemographic changes occurring in gentrifying neighborhoods generally correspond with simultaneous decreases in aggregate health risk behaviors and negative health outcomes. However, these changes are heterogeneous and complex. Whether and how neighborhood health changes alongside other components of neighborhood change depends on whether gentrification occurs in majority Black, Hispanic, or White neighborhoods. Our findings provide preliminary evidence that the changes accompanying gentrification extend to neighborhood health, but the direction of influence varies by neighborhood composition, type of sociodemographic change, specific health outcome, and spatial spillover. We discuss theoretical implications for future work addressing the mechanisms driving changes in neighborhood health, and potential approaches that differentiate policy responses.

Keywords

Gentrification; neighborhood change; neighborhood health; racial stratification; urban inequality

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Since Ruth Glass famously coined the term in 1964, gentrification has been the focus of much scholarly debate in academic, policy, and mainstream circles. A large body of work has documented this residential sorting process in which neighborhoods experience an in-migration of wealthier households and increased institutional investment into previously

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low-income neighborhoods, thereby transforming the social and economic fabric of these communities and reshaping the urban mosaic of cities across the United States. But despite decades of research on gentrification, relatively few studies have investigated explicit links between gentrification and neighborhood health (Gibbons et al., 2018). This study examines links between neighborhood health and gentrification—increases in a neighborhood's property values and sociodemographic conditions of the resident population relative to its metropolitan region. Gentrification is associated with decreases in neighborhood poverty and crime, increased amenities and municipal services, and other community improvements (Papachristos et al., 2011)—all of which are identified as social determinants of health (Williams et al., 2008). However, gentrification is also associated with population-level replacement of the existing community, or threats thereof, by an in-moving population that differs along sociodemographic lines. This raises the possibility that community improvements via gentrification may negatively impact current residents. For example, if the threat or perception of impending gentrification is linked to stress, it may lead to changes in health behaviors or other stress-linked health outcomes (Hirsch et al., 2021).

Tremendous interest in neighborhood health effects has also motivated concern about the directionality and heterogeneity of health effects due to neighborhood gentrification and the potential for interventions to improve neighborhood health (Diez Roux, 2004). A large and still-growing literature documents the negative health consequences of neighborhood deprivation or neighborhood poverty, particularly when it intersects with racial isolation and residential segregation (Riley, 2018). But there are multiple challenges to research efforts to clarify how gentrification influences neighborhood health. First, the question requires longitudinal data on both neighborhood change over time and neighborhood health over time. Second, the research must focus on health outcomes for which change is plausibly detectable in the study period. Third, the possibility of heterogeneous effects of gentrification on health can lead to inaccurate conclusions if not modeled explicitly. Our study overcomes these three challenges by combining census data with health survey data from two time points for a large sample of neighborhoods from the 10 most populous metropolitan areas in the U.S. to get a longitudinal understanding of the dynamic associations between local gentrification and health. We explore how changes in the sociodemographic conditions of gentrifying neighborhoods correlate with changes in neighborhood health by focusing on five adult health outcomes that are likely to be sensitive to neighborhood context. We explicitly model the spatial autocorrelation between changes in the primary neighborhood and surrounding neighborhoods in order to account for the potential that changes in gentrifying neighborhoods also transform health in nearby communities, and vice versa. Mindful of the complexity of neighborhood change, we explore how the changes in neighborhood health that follow gentrification vary by baseline neighborhood racial/ethnic composition, by the type of socioeconomic changes that accompany gentrification, and by health outcome, all while accounting for possible spatial spillover from surrounding neighborhoods. We explore these contingencies of the neighborhood change–neighborhood health association using stratified models, interaction terms, and spatial regression methods. Overall, our study finds significant differences between gentrifying and nongentrifying neighborhoods in their associations with neighborhood health—the neighborhood correlates of gentrification tend to change alongside decreases in unhealthy behaviors and negative health outcomes at an aggregate level. However, these neighborhood changes are heterogeneous and complex, and they depend on whether gentrification occurs in majority-Black, -Hispanic, or -White neighborhoods, as well as on the type of socioeconomic changes that accompany gentrification and on the domain of neighborhood health being assessed.

Background

Neighborhood Influence on Mental Health and Health Behaviors

Prior empirical studies aiming to quantify the impact of gentrification on health are difficult to summarize into broad conclusions (Smith et al., 2020). The literature linking neighborhood context to health can lead us to expect that gentrification might be bad for neighborhood health in some ways (Huynh & Maroko, 2014), and simultaneously good for neighborhood health in others (Agbai, 2021). Yet empirical studies based in the United States show generally null or inconsistent results, highlighting variation by resident and neighborhood characteristics (Gibbons & Barton, 2016; Smith et al., 2020). A thoughtful theoretical literature details the potential mechanisms through which gentrification can be harmful, especially for communities of color. The in-movement of newcomers from different sociodemographic and cultural backgrounds into gentrifying neighborhoods can result in disrupted social networks, fears of physical and cultural displacement, clashes over neighborhood norms, and withdrawal from longstanding neighborhood institutions (Candipan, 2019; Freeman, 2005; Fullilove & Wallace, 2011; Hyra, 2017). To the extent that gentrification is an exclusionary process, a disruptive process (disrupting protective social networks and institutional fabric through displacement), a stress-inducing event, a process that increases racially targeted surveillance by law enforcement, or one that lowers access to stable housing, gentrification is expected to undermine the social determinants of health and is likely to result in poor or worsening health for long-term residents. On the other hand, neighborhood health is socioeconomically patterned in ways that suggest gentrification may be good for neighborhood health. For instance, if gentrification brings more health-promoting amenities, economic investment, improved perceived safety, reduced crime/violence, increased access to healthy food/reduced access to fast food, reduced access to alcohol, and changing smoking norms/smoking policy to a neighborhood, it may lead to positive changes in health behaviors and mental health outcomes.

We assess the consequences of gentrification and neighborhood change for five measures of neighborhood health which are significant for morbidity and mortality, and which are understood to vary with neighborhood context: poor mental health, smoking, obesity, insufficient sleep, and binge drinking. The behavioral component in these health outcomes makes them especially likely to be sensitive to neighborhood gentrification processes in the short term. For example, availability of alcohol and tobacco as a function of the density of liquor stores and corner stores, as well as norms and regulations around smoking or drinking in public spaces, are aspects of the neighborhood environment that may prompt changes in behavior if altered through gentrification (Ahern et al., 2009; Campbell et al., 2009). We measured the five health outcomes at the neighborhood level to assess the relationships between changing neighborhood sociodemographics and changes in local health. Although this study is not designed to tease apart the effects of changing neighborhood context from the effects of changing neighborhood composition, there is still much to be inferred from the extensive literature on neighborhood effects on individual health about the potential for neighborhood change to impact these domains of health.

Prior research on the influence of gentrification on *mental health* has yielded mixed results. Some research suggests that residents of gentrifying neighborhoods experience more anxiety and depression than those in nongentrifying neighborhoods (Smith et al., 2018; Tran et al., 2020). There is also some evidence that displacement from a gentrifying neighborhood to a poor neighborhood is associated with worse mental health (Lim et al., 2017). Yet, in study of residents displaced by Hurricane Katrina, being displaced to a gentrified neighborhood was not associated with psychological distress (Schnake-Mahl et al., 2020). Mental health has also been shown to mediate the associations between neighborhood poverty and health behaviors such as sleep, diet, smoking, and alcohol consumption. But the associations are complex and bidirectional. In this sense, mental health is both a mechanism linking gentrification to neighborhood health and a health outcome, in itself. Health behaviors such as smoking and binge drinking, although detrimental to physical health, can simultaneously be protective for mental health by serving as a coping strategy (Jackson et al., 2010). Thus, neighborhood-level patterns in smoking and binge drinking may shift in response to instability and traumatic exposures in a way that buffers the impact of those stressors on mental health.

There has long been a socioeconomic gradient in *smoking* prevalence, as well as in cessation (Businelle et al., 2010). But it is less clear how neighborhood-level smoking prevalence changes in response to gentrification. Among long-term residents in gentrifying neighborhoods, social support, neighborhood disadvantage, and stress are mechanisms likely to mediate the positive association between neighborhood socioeconomic status (SES) and smoking cessation (Businelle et al., 2010). Among new residents in gentrifying neighborhoods, higher individual SES is likely to be associated with reduced smoking prevalence. Taken together, one might expect smoking prevalence to decline as neighborhood SES increases in gentrifying neighborhoods, but there is also evidence suggesting that after accounting for individuals' SES, neighborhood SES is not associated with individual smoking levels among adolescents (Mathur et al., 2013). Trends in smoking prevalence among adults are determined to a large degree by the neighborhood conditions (i.e., social norms, advertising, policies restricting smoking) that constrain or promote smoking initiation during adolescence and early adulthood (Henriksen et al., 2008, Glenn et al., 2017; Giovenco et al., 2020). Once a smoking habit is established, it is difficult to quit (Maralani, 2013). In this sense, smoking prevalence may be slower to respond to changes in neighborhood context than other health behaviors or outcomes. Because smoking is heavily stratified by educational attainment, it is possible that changes in smoking prevalence in gentrifying neighborhoods may reflect changes in neighborhood composition instead of changes in the smoking behavior of long-term residents. On the other hand, smoking behavior is shaped by local smoking norms (Glenn et al., 2017), the ability to avoid the stigma associated with smoking (McCready et al., 2019), and ease of access to cigarettes (Glenn et al., 2020), which vary by neighborhood SES.

The neighborhood built environment (e.g., fast food outlets and access to parks) and the neighborhood social environment (e.g., poverty and residential segregation) are both important domains of exposure that shape *obesity* over the life course through multiple mechanisms (Carroll-Scott et al., 2013; Papas et al., 2007; Suglia et al., 2016). Local social and cultural norms may play only a minor role in obesity prevalence (Hruschka et al., 2011; Park et al., 2008), whereas constraints on food access and limited access to safe places for physical activity are more consistently associated with obesity (Carroll-Scott et al., 2013). This is concerning because, on average, predominantly Black neighborhoods have disproportionate access to unhealthy foods (James et al., 2014). The consequences of longstanding racialized disadvantage on obesity do not appear to be easily reversed through stand-alone infrastructure changes, such as the opening of a new grocery store (Cummins et al., 2014). In addition to constraints on a healthy diet and physical activity, neighborhood context can also influence obesity indirectly through stress pathways, such as through the cumulative psychosocial stress that stems from exposure to neighborhood disadvantage (Burdette & Hill, 2008; Kwarteng et al., 2017; Tan et al., 2017). Psychosocial stress has been shown to alter metabolic functioning and the distribution of fat in the body (Björntorp & Rosmond, 2000), increasing central adiposity which puts individuals at further risk for cardiovascular disease and diabetes. One recent study examined trajectories of neighborhood SES over a 10-year period along with weight status, and found that increases in neighborhood SES were associated with lower likelihoods of excessive weight gain for individuals (Zhang et al., 2021).

Insufficient sleep is an important health outcome in its own right, as well as a contributor to other physical and mental health outcomes (Johnson et al., 2016). Insufficient sleep is associated with cardiovascular disease, obesity, insulin resistance, and even death (Grandner & Pack, 2011). Although the impact of gentrification on insufficient sleep is unknown, it is well established that neighborhood disadvantage and related neighborhood conditions are associated with poor sleep quality, even after controlling for individual characteristics (Fuller-Rowell et al., 2016; Troxel et al., 2020). Perceived neighborhood safety and neighborhood crime, noise, crowding, and commuting schedules are potential mechanisms linking neighborhood context to poor sleep quality (Grandner et al., 2010). More recent work suggests that even within a context of neighborhood disadvantage, poor housing conditions are also associated with shorter sleep duration and poor sleep quality (Troxel et al., 2020).

Binge drinking is associated with over half of the deaths due to excessive alcohol use in the United States each year, and it is associated with increased risk of alcohol dependence, hypertension, myocardial infarction, adverse birth outcomes, and suicide (NIAAA, 2000; Stahre et al., 2014). Similar to the other health risk behaviors, neighborhood context can shape binge drinking initiation, the motivation to consume alcohol, the availability of alcohol, and the acceptability of public drunkenness (Ahern et al., 2013; Chauhan et al., 2016; Hill & Angel, 2005). Higher density of alcohol outlets in a neighborhood is associated with a higher prevalence of binge drinking (Ahern et al., 2013). In addition to the direct impact of alcohol availability on binge drinking, neighborhood norms around drinking behavior may permit or inhibit binge drinking, and neighborhood poverty and violence, to the extent that alcohol consumption is a way of coping with anxiety and depression, may also indirectly increase binge drinking (Hill & Angel, 2005). But unlike insufficient sleep or obesity, binge drinking is not associated with neighborhood SES in straightforward ways. For instance, the prevalence of binge drinking initiation among adolescents has been found to be higher among those who perceive greater neighborhood safety (Tucker et al., 2013) and, among adults, binge drinking has been found to be more likely among adults in highly ordered neighborhoods (Tucker et al., 2021). As with our other health outcomes of interest, the mechanisms linking neighborhood context to binge drinking may vary by race. For example, neighborhood norms that are more accepting of drunkenness appear to be associated with greater binge drinking for Non-Hispanic Whites only (Chauhan et al., 2016). Few studies have explicitly examined the influence of gentrification on binge drinking, but a recent study by Izenberg et al. (2018) in California found that gentrification was only associated with binge drinking among residents who had lived in a neighborhood for less than five years, not those who had lived in a neighborhood longer. These findings suggest that any increase in binge drinking in gentrifying neighborhoods may reflect compositional changes more than changes in drinking patterns among long-term residents.

Heterogeneous Effects of Gentrification

Although often theorized as a singular process, the term *gentrification* can encompass a wide variety of neighborhood change. As such, the health consequences of gentrification are likely to vary depending on how specific features of neighborhood context and composition are transformed through gentrification. For instance, gentrification in one neighborhood may lead to an increase in neighborhood SES and changes in the proportion of residents who are foreign-born, whereas a different gentrifying neighborhood may experience an increase in neighborhood SES but no change in immigrant composition. These two neighborhoods are both gentrifying, but the mechanisms and consequences by which gentrification changes health in these two neighborhoods may be quite different.

Similarly, the health consequences of gentrification are also likely to vary according to a neighborhood's baseline characteristics (neighborhood sociodemographic characteristics, neighborhood history, region, whether it is predominantly Black, etc.). Mindful that gentrification, in the U.S. context, is an inherently racialized process, we do not assume that the gentrification–health link will be uniform regardless of neighborhood racial composition as baseline or the kind of racialized change that occurs in a gentrifying neighborhood. For example, in their study of Philadelphia, Gibbons and Barton (2016) find that although gentrification modestly improves self-rated health for residents overall, it tends to lead to worse health outcomes for Blacks. Prior work also suggests that across neighborhoods with different initial racial compositions, there are differences in the demographics of newly arrived residents (Owens & Candipan, 2019; Rucks-Ahidiana, 2020). Rucks-Ahidiana (2020) found that, in majority White neighborhoods that undergo gentrification, newcomers tend to have higher income. In contrast, in majority Black or Hispanic neighborhoods, newcomers tend to have higher levels of education, but not necessarily higher income. Using restricted census data for all metropolitan regions in the United States, however, Owens and Candipan (2019) found consistent patterns across different types of gentrifying neighborhoods. They found that recent movers into socioeconomically ascendant neighborhoods tended to be White and higher-SES, regardless of initial neighborhood racial composition; the share of White residents in majority Black, majority Hispanic, and predominantly White neighborhoods increased in ascending neighborhoods, but decreased in neighborhoods that did not ascend (Owens & Candipan, 2019). All said, gentrification changes racialization in that it changes how certain communities of color are racialized relative to Whites (Candipan, 2019; Huante, 2021). Finally, many kinds of neighborhood change occur outside of a gentrification process and yet still have consequences for neighborhood health.

Thus, there is likely no singular story of how gentrification changes neighborhood health, but rather many stories that can be different and yet also simultaneously true. By modeling multiple types of neighborhood change explicitly and in addition to gentrification, our study design allows us to clarify the ways that the changing health outcomes associated with gentrification vary depending on the co-occurrence of other kinds of neighborhood change.

Many of the mechanisms outlined above focus on potential causal links between gentrification and individual health outcomes, particularly for vulnerable populations. It is important to note that the current study examines aggregate, population-level shifts in health outcomes. As such, it is possible that population-level increases in socioeconomic status likely map onto better reported health because of population replacement. The models explored in the current paper cannot distinguish between these types of changes. Instead, we seek to identify significant relationships that warrant further inquiry.

Research Questions and Conceptual Model

Despite a large body of gentrification research, relatively few studies have examined the association between gentrification and neighborhood health (Agbai, 2021; Gibbons et al., 2018; Hyra et al., 2019). Ours is one of the only studies to document changes to neighborhood health occurring simultaneously with the changes accompanying gentrification using a large sample of neighborhoods from the 10 most populous metropolitan areas. We focus on the following three research questions:

1. Does neighborhood health change as neighborhood sociodemographics change?
2. (a) Does change in neighborhood health occur differently in neighborhoods experiencing gentrification relative to those that do not? (b) Which types of sociodemographic change are associated with changing neighborhood health in gentrifying neighborhoods?
3. Do these changes to neighborhood health depend on the initial racial composition of the neighborhood?

Building on these research questions, we hypothesize that gentrification will be associated with detectable changes in multiple health outcomes measured at the neighborhood level, but that the magnitude and direction of changes in neighborhood health will depend on several factors. Our study design centers on explicit modeling of four key sources of heterogeneity in the neighborhood health returns to gentrification. These sources of heterogeneity, along with the hypothesized pathways linking gentrification to neighborhood health, are visualized in the conceptual model that guides our analysis (Appendix Figure A1). Informed by prior literature, we hypothesize that initial neighborhood racial/ethnic composition and type of socioeconomic change will moderate the influence of gentrification on neighborhood health. We also hypothesize that spillover from the dynamics in surrounding neighborhoods will be a source of variance in the gentrification–neighborhood health association. The inconclusive literature on the gentrification–health association precludes predictions as to the direction of associations between gentrification and specific health outcomes, but we do have theoretical assumptions about the pathways that likely link gentrification to neighborhood health that are informed by the literature. Considering first the negative pathways, Hyra et al. (2019) articulate four ways that gentrification may lead to cumulative stress for long-term residents: heightened police monitoring, disruption of social support, loss of political power, and fear of displacement. They posit that the cumulative stress effect of these gentrification-induced neighborhood changes could increase unhealthy behaviors or poor health among low-income residents (Hyra et al., 2019). Considering next the positive pathways, scholars have documented the potential for gentrification-induced neighborhood investment to increase health-promoting amenities, although the potential for renewal through gentrification is constrained for majority-Black neighborhoods (Hwang & Sampson, 2014). Still, to the extent that gentrification increases health-promoting social norms and health-promoting resources available to residents, it may decrease unhealthy behaviors and improve health at the neighborhood level. Thus, a combination of positive and negative pathways from gentrification likely influence neighborhood health simultaneously. Mindful of the heterogeneity in the responsiveness of each health outcome to the various pathways as well as differences in the time scale required for detectable change, we expect to find varied associations with gentrification across the health outcomes we test. For example, neighborhood mental health is likely to be responsive to changing neighborhood conditions in the very short term, whereas obesity is likely to require a longer time horizon for effects to be detectable. Finally, informed especially by the sociological literature on gentrification (Hwang & Sampson, 2014), we hypothesize that declines in neighborhood health will be more likely in gentrifying neighborhoods with an initial racial composition that is not majority White, than in majority White neighborhoods, due to weaker trajectories of investment. By documenting the complexity of these dynamics in our conceptual model (Appendix Figure A1), we aim to highlight the contingent nature of neighborhood health and the ways disadvantages and advantages in health trends at the neighborhood level can been gained or lost in the face of gentrification depending on how it co-occurs with other moderating variables.

Data and Measures

Dependent Variables

To answer our questions, we draw on several administrative data sources. The dependent variables for our analyses are neighborhood health measures, drawn from the Centers for Disease Control and Prevention (CDC)'s PLACES project. The PLACES project is an extension of the CDC's 500 Cities Project, which resulted from a partnership between the CDC and the Robert Wood Johnson Foundation. This project expands the utility of the original 500 Cities data by providing first-ever estimates at multiple local-area levels (i.e., county, place, census tract, and zip code tabulation (ZCTA) levels) on health outcomes, unhealthy behaviors, and health prevention from 2013 to 2018.[1] Tract-level measures from the CDC-PLACES data were drawn from the CDC's Behavioral Risk Factor Surveillance System (BRFSS), a biannual national survey typically reported at the county and state levels, and derived via small-area estimation from multilevel models using a poststratification approach. The CDC tested the validity of this method by aggregating the local-area estimates up to the county level in select places and found that the measures produced by their method closely matched the raw county-level BRFSS estimates.

Constructing our dependent variable consists of two steps. Our analyses rely on five tract-level measures of aggregate neighborhood health. These dependent variables consist of measures capturing health outcomes, health status, and health risk behaviors (as categorized in the PLACES data). All measures report annual prevalence for the adult population (> 18 years and older) in a given tract for that wave.

For health outcomes, we rely on tract-level obesity prevalence estimates. *Obesity* is measured as the proportion of adult respondents who have a body mass index (BMI) of ≥30.0 kg/m^2. For health status, we rely on tract-level estimates of *poor mental health* prevalence, which is the proportion of adult respondents who self-report that their "mental health was not good" for 14 or more days during the past 30 days. Higher levels on both measures indicate worse health at the aggregate level. In addition to these two measures of health status, we analyze three health risk behaviors at the tract level. *Binge drinking* is measured as the proportion of the adult population who self-report having five or more drinks on an occasion for men, or four or more drinks for women, within the last 30 days. *Smoking* is the proportion of the adult population who self-report having smoked ≥100 cigarettes in their lifetime and currently smoking every day or some days. Finally, *insufficient sleep* is measured as the proportion of the population who self-report getting less than 7 hours of sleep, on average, during a 24 hour period, a condition associated with numerous chronic diseases and conditions. We selected these five outcomes because they are risk factors for more serious conditions and chronic diseases and are associated with thousands of deaths annually.

For all neighborhood health measures, we observe the prevalence rates in 2013 and again in 2018, representing the first and last waves of the CDC-PLACES project, to capture the change in these rates over time. The change from 2013 to 2018 for each neighborhood health measure becomes a dependent variable in our analyses. As such, higher values for all five dependent variables correspond to worsening neighborhood health. One noted limitation to the CDC-PLACES data is that they are crude rates and do not distinguish between health that began in adulthood versus health that began in childhood and continued into later years.

Categorizing Gentrification and Neighborhood Types

Data for key predictors and covariates were drawn from the 2000 and 2010 decennial census, and American Community Survey (ACS) 5-year estimates between 2008–12 and

[1] See https://www.cdc.gov/places/about/index.html for information about the origin and evolution of the project, its methodology, and the measures it provides at multiple geographic levels.

2015–19. Census tracts were normalized to 2010 boundaries using the longitudinal tract database (LTDB).

Our key predictor is a binary measure denoting whether or not a neighborhood gentrified from 2010 to 2018. Quantitative researchers have operationalized gentrification in different ways. We employ a threshold approach, influenced by prior work (Ding et al., 2016; Freeman & Braconi, 2004), which compares property values for a neighborhood to those in other neighborhoods within the same broader housing market over time. To construct our gentrification measure, we observe the median home value for a tract in 2010 and compare that value to the median home value for its metropolitan statistical area (MSA). A tract that is below the median in 2010 is eligible to gentrify. We then repeat this step for our end period, 2015–19. Tracts that change from below-MSA median home values in 2010 to above-MSA median home values in 2015–19 are classified as having gentrified.[2] All other tracts that remained below the MSA median for the duration of the observed period are classified as eligible to gentrify, but not gentrifying. Note that our analysis only observes neighborhoods that were eligible to gentrify in 2010—tracts with median home values above their MSA median were ineligible to gentrify and thus removed from our analysis.[3] This allows us to compare outcomes in neighborhoods with similar economic standing prior to our study period.

We also construct three binary measures that classify neighborhoods based on their predominant neighborhood racial composition in 2000—majority Black, majority Hispanic, and majority White. Specifically, we classify a neighborhood as majority Black (or majority Hispanic) if that tract's resident population in 2000 is more than 50% Black (or Hispanic). We categorize neighborhoods as predominantly ("majority") White when the tract population of Whites is more than 70%. We then include these dichotomous measures as key predictors in separate models (one for each majority racial composition type) to examine whether the association between gentrification, neighborhood change, and neighborhood health varies between predominantly Black and non-Black, Hispanic and non-Hispanic, and White and non-White neighborhoods (described below).

Covariates and Controls

We include a battery of temporally lagged measures that account for initial neighborhood context 1 year prior to our study period. These measures are derived from ACS 2010–2014 estimates, with the midpoint (2012) representing one year prior to the CDC's initial collection wave for health measures from the 500 Cities project (in 2013).

In addition to baseline neighborhood context, we also include measures capturing various components of neighborhood compositional change from 2010–14 to 2015–19, driven by prior work showing their relationship to community and neighborhood health. These

[2]. Empirical definitions of gentrification vary, and there are limits to the aspects of gentrification that quantitative data can capture (e.g., changes to neighborhood norms and culture; etc.). As a sensitivity check, we conducted analyses using an alternative composite index of gentrification that captured neighborhood socioeconomic ascent via factor analysis, following past work (Candipan and Bader, 2022; Owens, 2012), and our main patterns held.

[3]. In alternative analyses, we performed models using a three-category neighborhood type measure that included tracts that were ineligible to gentrify.

neighborhood sociodemographic change measures include the change in neighborhood proportion White, proportion foreign-born, proportion with a college degree, and proportion of owner-occupied households. We also include the change in median home value. Although we use information on median home value to classify neighborhoods into gentrification categories, by including this change measure for median home value we are able to observe how smaller or larger increases in median home value from 2010–14 to 2015–19 are associated with changes in neighborhood health. Moreover, an increase in home value over time does not guarantee that a neighborhood gentrifies; thus, the change measure for median home value provides information about neighborhood change above and beyond gentrification.

Sample

We restrict our sample to tracts in the CDC 500 Cities data that are located within the 10 most populous MSAs (in 2010).[4] We then further narrow the focus to tracts that were considered eligible to gentrify in 2010.[5]

Analytic Strategy

To investigate our research questions, we perform a series of spatial autoregressive (SAR) models that examine how gentrification and contextual features in neighborhoods change simultaneously alongside neighborhood health using a two-time-point longitudinal design. To do so, we first specify how neighborhoods relate to one another. In all analyses, we define neighborhoods as census tracts, following most neighborhood-focused quantitative research. We recognize that census tract boundaries, although convenient, can be somewhat arbitrary. Our spatial models are motivated partly by an intent to account for the spatial structure of the data that might arbitrarily cluster values together simply because of the way boundaries are drawn.

We construct our spatial weights matrix using a queen's first-order contiguity definition with spectral normalization. The queen's first-order weights matrix takes a given tract and observes all census tracts that share a border or vertices as a "neighbor," weighting these neighboring tracts in the matrix for that row. We then employ our spatial weights matrix (W) for all analyses.

We perform a series of generalized two-stage least squares SAR models (Kelejian & Prucha, 1998, 2010), an approach that is robust to normality assumptions, to examine how gentrification and changes in neighborhood composition correspond to changes in neighborhood health and unhealthy behaviors. In all models, we include a spatial lag term for the dependent variable that we estimate by including information on the spatial structure

4. We calculated the total 2010 population of all metropolitan tracts within census-designated MSAs (2003 Office of Management and Budget (OMB) definitions). The 10 MSAs are the following: Atlanta–Sandy Springs–Marietta, GA; Chicago–Naperville–Joliet, IL; Dallas–Plano–Irving, TX; Houston–Baytown–Sugar Land, TX; Los Angeles–Long Beach–Glendale, CA; New York–Wayne–White Plains, NY–NJ; Philadelphia, PA; Phoenix–Mesa–Scottsdale, AZ; Riverside–San Bernardino–Ontario, CA; Washington–Arlington–Alexandria, DC–VA–MD–WV.

5. The sample data and a replication code will be hosted on the author's website and available to the research community.

of the data through our spatial weights matrix. This allows us to account for the spatial autocorrelation in neighborhood health that occurs via spillover from nearby areas.[6]

We begin with models that provide an initial portrait of the relationship between gentrification and neighborhood health. This is expressed as:

$$y_{\mathrm{i(t2-t1)}} = \lambda W y_{i(t2-t1)} + \beta_1 \mathrm{Gentrification} + X\beta_2 + \beta_3 \mathrm{BaseHealth} + \varepsilon \tag{1}$$

where y is the change in prevalence rates (for each neighborhood health measure) in tract i from 2013 (t_1) to 2018 (t_2). We include a spatial lag parameter ($\lambda W y$) on our dependent variable, which we estimate via our spatial weights contiguity matrix (W). The spatial lag term can be positive (indicating a "spread" effect; e.g., spillover initiated by interaction in neighboring areas) or negative (indicating a "backwash" effect; e.g., surrounding areas might draw away resources or amenities that affect neighborhood health).

Our focal predictor is our binary indicator (*gentrification*) classifying whether a tract gentrified from 2010 to 2015–19. X represents our vector of neighborhood contextual measures capturing initial sociodemographic composition and change, which we include in all models. We also control for baseline neighborhood health prevalence (*BaseHealth*) in 2013. Because the processes and conditions generating the relationship between gentrification and neighborhood health may vary between MSAs, our analyses also include MSA fixed effects to account for any unobservable higher-level factors that might be endogenous to our outcomes of interest, and would also adjust for sociodemographic differences between places.[7] These models indicate which factors correspond to changes in neighborhood health, how neighborhood composition is associated with simultaneous changes in neighborhood health, and whether gentrifying and nongentrifying neighborhoods differ significantly in their relationship to changes in neighborhood health.

Next, we analyze whether the corresponding changes in neighborhood characteristics and neighborhood health differ significantly between gentrifying neighborhoods relative to those that were eligible to gentrify, but did not. We do so by adding interactions between our neighborhood change measures and gentrification.

$$y_{(ti2-ti1)} = \lambda W y_i + \beta_1 \text{ Gentrification } + X\beta_2 + \beta_3 \mathrm{BaseHealth} + \beta_4 \text{ Gentrification } * \text{ NeighChange } + \varepsilon \tag{2}$$

The coefficient for the interaction (Gentrification*NeighChange) indicates whether the magnitude and direction of the effect of neighborhood change on changing neighborhood health varies in gentrifying and nongentrifying neighborhoods.

6. We do perform a spatial ordinary least squares regression, but global Moran's I tests indicate that conditioning for neighborhood context and MSA fixed effects does not remove the significant spatial autocorrelation in our models.
7. An alternative approach to the fixed effects specification would be to perform separate spatial regression models for each metropolitan area. We do also perform models without MSA fixed effects. These results are available upon request.

Finally, we ask whether the relationship between gentrification and changing neighborhood health is heterogeneous across different types of neighborhoods with varying initial racial composition. Specifically, we examine whether the association between gentrification and neighborhood health looks different in initially majority Black, initially majority Hispanic, and initially majority White neighborhoods. Again, for these neighborhood classifications, we define “initially majority” as tracts with a share of a given racial/ethnic population that is greater than 50% in 2000 (e.g., majority Black tracts are those with >50% Black residents in 2000, and so on).[8] After classifying neighborhoods into binary categories (e.g., majority Black vs. nonmajority Black), we add these measures to our model and interact them gentrification. We perform separate models for each neighborhood type (majority Black, Hispanic, and White). These models take the following form:

$$y_{(ti2-ti1)} = \lambda W y_i + \beta_1 \text{Gentrification} + X\beta_2 + \beta_3 \text{BaseHealth} + \beta_3 \text{NeighChange} + \beta_4 \text{Gentrification*MajRace} + \beta_5 \text{MajRace} + \varepsilon \quad (3)$$

The interaction between gentrification and neighborhood majority race type indicates whether the relationship between gentrification and simultaneous change in neighborhood health differs significantly between majority Black and nonmajority Black neighborhoods, between majority Hispanic and nonmajority Hispanic neighborhoods, and between majority White and majority non-White neighborhoods.

The overall goal of our models is to identify: (1) how gentrification is related to simultaneous changes in aggregate health risk behaviors, health status, and health outcomes in neighborhoods; (2) how different components of neighborhood change differently shape this relationship; (3) and whether these associations play out differently in majority Black, majority Hispanic, and majority White neighborhoods.

Before arriving at our SAR models, we first tested for spatial autocorrelation in our models by performing Moran’s I tests on ordinary least squares regression model residuals to ensure that we were not violating the assumptions of ordinary least squares. Across all models, the Moran’s I value was positive and significant, indicating a spatial pattern in the regression residuals after conditioning for neighborhood factors. We also performed Lagrange multiplier (LM) tests, which confirmed our analytic strategy of including a spatial lag term for the dependent variable. The LM test did not recommend the spatial error model, indicating that there was not significant spatial structure to the error, and we therefore did not include the spatial error term in our models after accounting for neighborhood-level covariates and MSA fixed effects.

8. We tested a definition of majority White that relied on the raw majority (>50%) and patterns held. In addition to providing more reliable estimates, our preferred definition of majority White (>70%) more closely aligns theoretically with past work that does not use a simple majority for White but instead relies on thresholds based on the national racial composition and distribution of neighborhood racial composition (Galster et al., 2003; Owens & Candipan, 2019). We also performed robustness tests using a 2010 definition for neighborhood majority race, and broader patterns of effect heterogeneity held. Neighborhoods carry racial legacies that are durable and shaped over time; hence, we used an earlier year to capture neighborhood majority racial composition using an earlier time point.

Limitations

Gentrification is driven by the movement of residents with differing socioeconomic profiles into and out of neighborhoods. That said, our tract-level analysis is unable to distinguish between changes in neighborhood health that are driven by individual-level processes (i.e., which health factors are changing due to incoming gentrifiers, longtime residents, or both). Although this limits our inference to aggregate effects, we are able to provide overall descriptive insights, with a wide geographic scope, about how changes accompanying gentrification relate to changes in neighborhood health.

Results

Descriptive Overview of Analytical Sample

Table 1 displays descriptive statistics for our dependent variables, key predictors, and related measures. Recall that our analytical sample is restricted to tracts that were eligible to gentrify. Just under 7% of eligible tracts gentrified from 2008–12 to 2015–19 using our definition—that is, tracts with median home values below their MSA median in 2008–12 had median home values above the MSA median by 2015–19. Just over one fifth of tracts in our sample that were eligible to gentrify had a majority Black resident population in 2000 (22.9%), a little over a seventh had a majority White population (15.4%), and nearly a third had a majority Hispanic population (29.2%).

The lower panel of Table 1 also shows global Moran's I values for baseline health prevalence measures as well as their associated change in prevalence rates from 2013 to 2018, with the latter representing the dependent variables for our models. Global Moran's I values can range from −1 to 1, indicating either negative or positive spatial autocorrelation against the null hypothesis of spatial randomness (the expected value of Moran's I under the null hypothesis is negative, but effectively zero). Global Moran's I values closer to −1 indicate strong negative spatial autocorrelation (spatially structured dissimilarity) whereas values closer to 1 indicate substantially strong spatial clustering of similar values.

We find statistically significant ($p < .001$) positive spatial autocorrelation for all baseline and change measures of neighborhood health in our analytical sample. This indicates that neighborhoods with higher aggregate prevalence (associated with worse neighborhood health) of the five health outcomes in our sample tend to be clustered near other neighborhoods with higher values, and vice versa—neighborhoods with lower prevalence rates tend to be located near other neighborhoods with lower rates. Baseline and change in the prevalence of sleep (Moran's I = 0.85 and 0.82), obesity (Moran's I = 0.84 and 0.63), and binge drinking (Moran's I = 0.74 and 0.62) all exhibit very strong positive spatial autocorrelation. Baseline smoking and poor mental health prevalence are also strongly spatially clustered among neighborhoods with similar values (each with Moran's I = 0.75), but the change in smoking and poor mental health prevalence rates display more modest positive spatial autocorrelation (Moran's I = 0.38 and 0.49, respectively). Overall, there is evidence suggesting that our outcomes of interest are not distributed across space randomly—geography matters for understanding aggregate health at the neighborhood level.

Type of Sociodemographic Change and Changing Neighborhood Health

Our first research question asks whether neighborhood health changes as neighborhood sociodemographic composition changes. To answer this question, we perform separate cross-sectional SAR models for each of our five neighborhood health outcomes. Table 2 displays results from SAR models for each of our five neighborhood health outcomes (Equation 1). All models control for a battery of initial neighborhood characteristics (temporally lagged one year prior to baseline) that capture landform, demographic characteristics, and socioeconomic composition in 2010–2014. Recall that higher values for each of the neighborhood health prevalence rates indicate higher levels of negative health status, health outcomes, and health risk behaviors. Because our measures capture the change in these neighborhood health outcomes over time, any positive coefficient corresponds to a worsening trend in aggregate health status or unhealthy behaviors.

Controlling for gentrification and baseline neighborhood factors, we observe that increases in different components of neighborhood SES generally correspond with a decrease in the prevalence of negative health outcomes, negative health status, and health risk behaviors. Increase in a neighborhood's college-educated population is largely associated with simultaneous improvements in aggregate health risk behaviors and mental health in a neighborhood. Increase in the percentage of residents with a bachelor's degree significantly correspond with substantial decreases in neighborhood-level obesity, smoking, insufficient sleep, and poor mental health. On the other hand, and perhaps contrary to expectations, increases in the college-educated population in a neighborhood correspond with increases in binge drinking prevalence. The associations between increasing proportion of homeowners and changes in neighborhood health risk behaviors and poor mental health parallel the associations described for the increase in college-educated residents—increase in the proportion of owner-occupied households corresponds with decreases in obesity, smoking, and poor mental health, but with increases in binge drinking prevalence. Increase in median home value is significantly associated with contemporaneous decreases in the proportion of people reporting poor mental health or smoking ($p < .10$). However, increases in median home value are significantly positively associated with an increasing proportion of people reporting insufficient sleep and binge drinking from 2013 to 2018.

Taken together, these findings suggest that increases in neighborhood socioeconomic status are associated with improvements in several key health outcomes and health risk behaviors, with the exception of: (1) binge drinking, which is positively associated with increases in median home value ($p < .10$), increases in the proportion of college-educated residents and proportion of owner-occupied houses; (2) insufficient sleep, which is positively correlated with median home values.

Models from Table 2 also include a binary measure denoting whether or not a neighborhood gentrified from 2010 to 2015–19 (among those eligible to gentrify in 2010). Gentrification is associated with a decreasing proportion reporting insufficient sleep, and decreasing prevalence of binge drinking and smoking, although the latter two only reach trend-level significance ($p < .10$).

Accounting for Spillover Effects of Surrounding Neighborhood Health

The spatial lag term captures the neighborhood spillover for each of our neighborhood health outcomes. Essentially, this term represents the weighted average of the neighborhood health changes and accounts for clustering in terms of similar changes that are occurring in nearby areas.

Note that although we can observe whether significant relationships exist between neighborhood context and neighborhood health, as well as the direction of that association, precisely interpreting the coefficients in a spatial lag model differs from standard ordinary least squares and requires that we compute the direct and indirect effects (LeSage & Pace, 2009). We illustrate this in Appendix Table A1, which decomposes the coefficients from our cross-sectional spatial lag models from Table 2 into direct, indirect, and total effects.[9] Direct effects are the marginal effects. These coefficients represent the effect of neighborhood composition and change in the focal neighborhood on its changes in unhealthy behaviors, physical, and mental health. Indirect effects represent the "spillover" effects—the effect of conditions occurring in nearby neighborhoods. These coefficients account for the effects of initial neighborhood context and neighborhood change in the surrounding census tracts on the changes in aggregate health in the focal neighborhood. Combining direct and indirect effects will yield the total effect of each covariate.

As one would expect, direct effects exert substantially more influence on changing neighborhood health. We present the effect decomposition to remind readers of the multiplier effect involved in spillover models that results in infinite reciprocal feedback loops—that is, as neighborhood characteristics change in the focal area, they affect nearby neighborhoods, which in turn feed back and affect the focal neighborhood, and so on. Nonetheless, the raw coefficients produced by spatial lag models allow us to glean important information about the relationship between neighborhood change, gentrification, and neighborhood health.

How Is Neighborhood Sociodemographic Change Associated With Neighborhood Health in Gentrifying Neighborhoods?

Next, we examine whether the association between simultaneous changes in neighborhood composition and neighborhood health differs between gentrifying and nongentrifying neighborhoods. The various components of neighborhood change could correspond differently in gentrifying and nongentrifying neighborhoods, which our next models investigate.

Table 3 displays coefficients from a spatial lag model that includes interactions between gentrification, our key neighborhood predictor, and specific types of sociodemographic change from 2010–14 to 2015–19 (Equation 2). As with the previous analyses, all models control for initial neighborhood composition (in 2010–14) and baseline neighborhood health (in 2013, the first collection year for CDC 500 Cities data), and account for spatial spillover and unobservable MSA-level factors that violate residual independence. The main effect of

[9] Models in Appendix Table A1 are presented for illustrative purposes and differ from Table 2 in that they do not contain MSA fixed effects.

gentrification is not significantly associated with changes in neighborhood health outcomes or health risk behaviors. However, when we observe the interaction of gentrification and neighborhood sociodemographic change, a more nuanced portrait emerges in the relationship between gentrification and neighborhood health. The interaction term between gentrification and increase in neighborhood proportion White is statistically significant and negative in direction for obesity, smoking, and mental health from 2013 to 2018. Given that the gentrification main effect is also negative for these three measures, the models indicate that gentrification accompanied by an increase in the non-Hispanic White population corresponds to significantly different associations with neighborhood health in gentrifying versus nongentrifying neighborhoods—gentrifying neighborhoods experience greater corresponding decreases of these adverse outcomes relative to nongentrifying neighborhoods.

The associations between different types of changes in neighborhood SES and changes in neighborhood health also depend on whether or not a neighborhood experiences gentrification. For insufficient sleep and mental health prevalence, the relationship between increasing median home value and changes in neighborhood health also differs significantly between gentrifying and nongentrifying neighborhoods—the interaction term for insufficient sleep is negative (and the main effect is positive), indicating decreases in its prevalence in gentrifying neighborhoods but increases in nongentrifying neighborhoods; the interaction term for poor mental health is positive (and the main effect is negative), indicating that rising home values reduce the association between gentrification and decreasing prevalence of poor mental health. An increasing share in a neighborhood's college-educated population corresponds with simultaneous increases in the prevalence of binge drinking in nongentrifying neighborhoods, but the increase is lower in gentrifying neighborhoods. An increasing presence of college-educated residents is negatively associated with declines in smoking prevalence in all neighborhoods, but the magnitude is stronger in gentrifying neighborhoods. An increasing share of foreign-born residents is associated with simultaneous increases in the prevalence of poor mental health in nongentrifying neighborhoods, but decreasing prevalence in gentrifying neighborhoods (although the interaction and gentrification main term are not statistically significant). In sum, SES change and increases in proportion White in gentrifying neighborhoods are associated with declines in both health risk behaviors and poor health status. However, these same changes are correlated with either worsening or attenuated outcomes in nongentrifying census tracts.

Do Changes to Neighborhood Health Depend on the Initial Racial Composition of the Neighborhood?

Next, we ask whether changes in neighborhood health depend on the interaction between gentrification and neighborhood racial composition. Our models include binary measures denoting whether a neighborhood is majority Black (or nonmajority Black), majority Hispanic (or nonmajority Hispanic), and majority White (or nonmajority White). Recall that we classify a tracts as "majority" based on their initial racial composition in 2000. We perform separate models for each neighborhood type. These models include both a main effect of neighborhood racial composition type and the interaction with gentrification.

Table 4 displays results comparing majority Black and nonmajority Black tracts. Gentrification appears to have different associations with neighborhood health in majority Black neighborhoods relative to nonmajority Black neighborhoods—it is generally associated with greater decreases in negative health aspects relative to nongentrifying neighborhoods, with an even greater reduction in initially majority Black neighborhoods. Although initially majority Black neighborhoods are associated with an increase in obesity prevalence ($p < .10$), the increase is less pronounced in Black neighborhoods experiencing gentrification. Gentrifying neighborhoods experience decreases in the prevalence of insufficient sleep, and this decrease is even greater in Black gentrifying neighborhoods. Majority Black neighborhoods undergoing gentrification also experience a greater concurrent decrease in smoking prevalence than nongentrifying Black neighborhoods, with both experiencing greater decreases in proportion smoking than all non-Black neighborhoods. Although not statistically significantly different, the patterns for binge drinking and mental health in majority Black gentrifying and nongentrifying neighborhoods parallel what we find for smoking, obesity, and insufficient sleep.

Table 5 compares majority and nonmajority Hispanic census tracts. As with majority Black models, the relationship between gentrification and neighborhood health seems to depend on whether a neighborhood is initially majority Hispanic. Majority Hispanic neighborhoods tend to experience significant increases in obesity prevalence. This increase, however, is smaller in Hispanic neighborhoods experiencing gentrification during this period. Although Hispanic neighborhoods experience a decrease in poor mental health from 2013 to 2018, the decrease is more pronounced in gentrifying Hispanic neighborhoods. Unlike majority Black models, gentrifying Hispanic neighborhoods are not always associated with reductions in aggregate health risk behavior. Although *nonHispanic* gentrifying neighborhoods are associated with decreases in binge drinking, all factors considered, the relationship reverses in majority Hispanic neighborhoods which experience an increase in binge drinking prevalence as they gentrify.

Finally, Table 6 compares majority White and nonmajority White gentrifying neighborhoods. All factors considered, majority White neighborhoods tend to be associated with decreases in negative aggregate health from 2013 to 2018. Initially majority White neighborhoods are negatively associated with increases in insufficient sleep, obesity, poor mental health, and smoking ($p < .10$) prevalence, holding all covariates constant and accounting for spatial spillover. However, with the exception of obesity, the negative associations are even greater in *non-White* neighborhoods experiencing gentrification relative to White gentrifying neighborhoods.

All considered, results from Tables 4–6 suggest that the interplay between gentrification and neighborhood racial composition is most salient in majority Black and majority Hispanic neighborhoods, and that the magnitude and direction of the association with gentrification depends on initial majority racial composition. Failing to account for both different initial neighborhood racial/ethnic composition and different gentrification types masks the nuanced relationship between neighborhood change and neighborhood health.

Discussion and Conclusion

Using tract-level estimates from the CDC-PLACES project linked to contextual data from the decennial census and ACS for the 10 largest MSAs, this study set out to understand how neighborhood health outcomes change as neighborhood sociodemographics change. Our study is one of the first to document the relationship between neighborhood health and neighborhood change in cases of gentrification, including variation in gentrification by baseline racial/ethnic populations and socioeconomic characteristics. Our results reveal how the sociodemographic and economic changes occurring in gentrifying neighborhoods largely co-occur with decreases in unhealthy behaviors and negative health outcomes. For instance, we find that increases in neighborhood SES, namely proportion college-educated, proportion of owner-occupied homes, and median home value, are associated with improvements in most of the health behaviors and outcomes we tested. We also find that, although gentrification in and of itself is rarely a significant predictor of the health outcomes studied here, the relationship between neighborhood socioeconomic change and neighborhood health varies by specific health outcome. Our results also suggest that initial neighborhood racial composition significantly modifies the relationship between neighborhood change and health outcomes. Taken together, this study extends previous efforts to clarify how gentrification changes neighborhood health by underscoring four key sources of heterogeneity in the health returns to gentrification: neighborhoods' initial racial/ethnic composition; type of sociodemographic neighborhood change; specific health outcome; and spatial spillover from surrounding neighborhoods.

First, gentrification processes appear to vary by the initial racial/ethnic composition of the neighborhood. For instance, a neighborhood that has a majority Hispanic composition prior to gentrification will see distinct shifts in neighborhood health compared to a neighborhood with a majority Black composition prior to gentrification. As such, whether and how neighborhood health changes along with other types of neighborhood compositional change depends on the interaction between initial racial composition and gentrification. Prior research suggests that this may be due to lower and slower trajectories of investment in gentrifying neighborhoods with a higher proportion of Black residents than other gentrifying neighborhoods (Hwang & Sampson, 2014). But even when gentrification does bring new resources, there is some evidence that Black long-term residents are excluded from the anticipated health benefits (Gibbons & Barton, 2016). Gibbons and Barton (2016) suggest this may be due to negative health impacts from the particularly harmful cultural displacement experienced by Black long-term residents in gentrifying neighborhoods.

Second, our findings show that the various components of neighborhood sociodemographic change accompanying gentrification have differing relationships with neighborhood health. We find that increases in proportion college-educated, proportion of households that are owner-occupied, and median home value have related but distinct associations with neighborhood health in gentrifying neighborhoods (which are again, distinct from their influences on nongentrifying neighborhoods). These results raise questions about the nature of the socioeconomic gradient in neighborhood health. Although there is a well-established linear relationship between neighborhood SES and neighborhood health, questions remain as to how closely coupled neighborhood SES and neighborhood health are in the short term.

We interpret our findings of null associations between increasing neighborhood SES and some health outcomes, and even a negative association between increasing neighborhood SES and neighborhood binge drinking, as evidence that the association between increasing neighborhood SES and neighborhood health, especially in settings of gentrification, is not straightforward. Indeed, a recent study observed that an increase in neighborhood SES was not associated with lower risk of colorectal cancer, as one might expect (Zhang et al., 2019). Our mixed results could be interpreted as support for the hypothesis that it takes more than incremental increases in one domain of neighborhood SES to transform neighborhood health in detectable ways in the short term. It is also likely that there are time lags between various kinds of neighborhood socioeconomic change and related changes in neighborhood health that preclude detecting changes to health in the short term.

Third, by studying the influence of neighborhood change on five different domains of neighborhood health, we demonstrate that any conclusions about the health returns to gentrification will vary depending on how health is measured. This may help in explaining why previous efforts to answer the question *Is gentrification good or bad for neighborhood health?* have often led to contradictory results (Gibbons & Barton, 2016; Schnake-Mahl et al., 2020). We find support for our hypothesis that the new investments and amenities that arrive in gentrifying neighborhoods are likely to be more relevant for some health outcomes than others and that the influx of new residents may shift social norms around health behaviors in different ways. For example, our results suggest that an increase in the percentage of non-Hispanic White residents in gentrifying neighborhoods is associated with an increase in binge drinking prevalence, but a decrease in the prevalence of smoking. These opposite trends for binge drinking and smoking are likely driven by a confluence of compositional and contextual neighborhood change. It is well established that binge drinking is consistently higher among non-Hispanic Whites (Kanny et al., 2013) and smoking is heavily stratified by educational attainment (Maralani, 2013). Thus, it is likely that our observed trends in this particular model of gentrifying neighborhoods reflect changes in neighborhood composition via the influx of higher SES, White residents. At the same time, there is compelling evidence that binge drinking increases with neighborhood income inequality as well as the local availability of alcohol, be it in liquor stores or bars (Ahern et al., 2013; Reilly et al., 2019). Similarly, smoking behavior is shaped by local smoking norms (Glenn et al., 2017), the ability to avoid the stigma associated with smoking (McCready et al., 2019), and ease of access to cigarettes (Glenn et al., 2020) – all contextual factors likely to vary with different types of neighborhood change and add to compositional effects. Although our study cannot settle the context versus composition debate (Ross & Mirowsky, 2008), our results do demonstrate just how complex and contingent the links are between neighborhood change and various neighborhood health outcomes.

Finally, our study highlights the importance of considering the spatial structure in our neighborhood-level analysis. Given the processes and policies that have created durably segregated neighborhoods in U.S. cities, it stands to reason that the clustering of tracts with similar attributes would shape behavior similarly across neighborhoods through shared interactions and movement. Neighboring communities are unlikely to be independent of each other; thus, there is strong reason to suspect spatial dependence, particularly in an analysis of neighborhood health where health-promoting and health risk behaviors may spill over past tract boundaries. Put simply, geography matters for understanding any associations between gentrification, neighborhood change, and health.

In summary, previous research into gentrification's influence on health often treats it as a homogeneous process. However, we demonstrate that the relationship between gentrification and neighborhood health is quite heterogeneous and complex. Findings from our study provide preliminary evidence that the changes accompanying gentrification do extend to neighborhood health outcomes, but the direction of influence varies by neighborhood composition, type of socioeconomic change, specific health outcome, and spatial spillover. Whether these changes in neighborhood health are driven by the displacement of longtime residents and an influx of healthier high-SES residents or by an increase in resources and accessible health services (or some combination of both) is a line of inquiry that we cannot address using aggregate-level data. We stress that our aims are descriptive and illustrative. Our findings set the stage for future work to analyze the mechanisms underlying these trends. We encourage researchers with more detailed individual-level data to build on this line of inquiry.

We focused on how different types of gentrification relate to health outcomes and health risk behaviors assessed at the neighborhood level. Future work could also investigate how gentrification corresponds to simultaneous changes in the prevalence of health prevention in neighborhoods, such as health insurance coverage, proactive health screenings, and routine doctor visits, among other preventative efforts. Whereas our study compares gentrifiable and gentrifying neighborhoods, future research could examine whether neighborhood health in gentrifying areas ultimately mirrors the relationship in longstanding high-income neighborhoods. Additionally, our focus on large, populous metropolitan regions leaves the door open for work to investigate whether the spatial data generating processes related to gentrification and changing neighborhood health look different in smaller, less populous areas. Further, although our analysis provides a bird's eye view of the spatialized relationship between gentrification and neighborhood health, we trade off the specificity inherent in a local analysis of these spatial processes. Finally, we observed changes in neighborhood composition and health over a roughly 5-year period, which may not be a long enough time frame to observe substantial changes in certain health outcomes (Ellen et al., 2001). Researchers with access to wider-reaching longitudinal data should investigate how gentrification and changes in neighborhood health outcomes and behaviors play out over a more extended period of time.

Note that our models rely on an indicator of gentrification that built on a perceived measure from the census (i.e., home values, which is self-reported by homeowners), which could have implications for our findings. Given that our study period coincided with the fallout of the Great Recession and the ensuing housing crisis, with racially patterned impacts that hit Black and Hispanic communities the hardest (Rugh & Massey, 2010), it could be the case that homeowners' perception of property values was lower than their actual values in majority Black and Hispanic neighborhoods. On the flip side, as gentrification occurs in a neighborhood, it is possible that homeowners may overestimate the value of their home as their neighborhood experiences socioeconomic upgrading. Although this would affect the degree to which we observe an increase in neighborhood housing values, we would likely still capture neighborhoods that are undergoing meaningful economic ascent.

Results from our study will be of interest to policymakers considering neighborhood revitalization initiatives and similar programs as a means of improving community health and well-being. Our findings show that improvements in neighborhood health in the short term do not consistently co-occur with increasing median household incomes. It is possible that the full consequences of neighborhood sociodemographic change and gentrification for neighborhood health take longer than five years to manifest. Our finding that binge drinking can increase in settings of gentrification, especially paired with recent evidence that neighborhood income inequality associated with alcohol-related emergency department visits (Reilly et al., 2019), offer a warning to policymakers to the effect that increasing neighborhood SES can pose new public health challenges. Our finding that neighborhood health is not sealed off from the influence of nearby neighborhoods should encourage local health officials to closely monitor health in the neighborhoods that surround those experiencing gentrification. The evidence of spatial spillover could also motivate local health departments to target interventions at multiple adjacent localities in order to improve neighborhood health. Policymakers should aim to ensure that longtime residents are buffered from the stresses of displacement and social network disruption and are benefiting from any improvements accompanying gentrification, by using tools such as affordable housing policies and zoning (Hyra et al., 2019). Most of all, policymakers should be mindful that when it comes to the health returns to gentrification, one size does not fit all. One cannot assume that just because gentrification was associated with reductions in smoking and binge drinking in one neighborhood the same will be true for another. Further, although neighborhood health may appear to improve with increasing neighborhood SES and gentrification, there are connected, yet often invisible, disadvantages in health for the people displaced which are rarely captured in studies of neighborhood change (Sims, 2021). Information about the spatial patterning of health and supportive programs that follow individual residents over time might also help strategic efforts to target responsive and proactive measures to specific communities and population groups, as well as site services and infrastructure, more effectively.

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Appendix

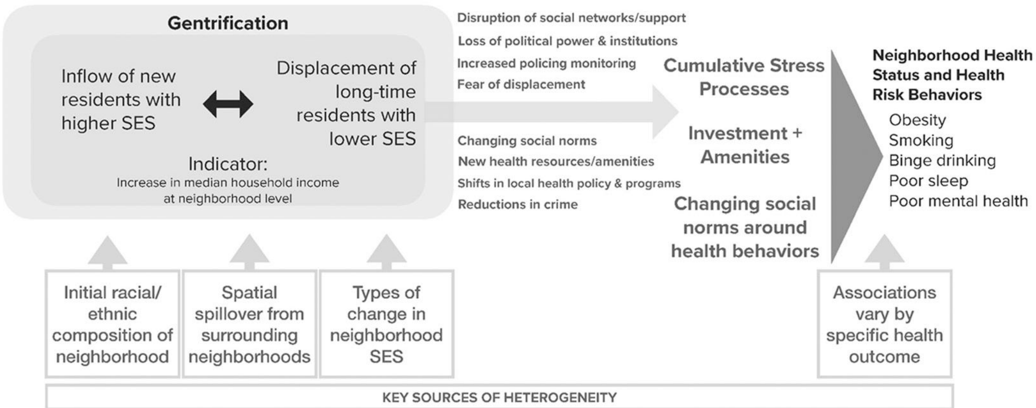

Figure A1.

The heterogeneity of neighborhood health returns to gentrification—conceptual model.

Note: SES refers to socioeconomic status.

Table A1.

Decomposition of the direct and indirect effects of select neighborhood characteristics on neighborhood health.

	Insufficient sleep			Obesity			Binge drinking			Smoking			
	Direct	**Indirect**	**Total**	**Direct**	**Indirect**	**Total**	**Direct**	**Indirect**	**Total**	**Direct**	**Indirect**	**Total**	**D**
Neighborhood change													
Δ % Non-Hispanic White	**−1.130**	**−0.153**	**−1.284**	−0.497	−0.022	−0.520	−0.182	−0.009	−0.191	−0.733	−0.015	−0.748	−(
Δ % Foreign born	**−1.194**	**−0.162**	**−1.356**	−0.753	−0.034	−0.787	*−0.536*	−0.027	*−0.563*	0.342	0.007	0.349	(
Δ Median home value (in 10,000s)	**0.008**	**0.001**	**0.009**	−0.005	0.000	−0.005	**0.006**	*0.000*	**0.006**	*−0.007*	0.000	*−0.007*	−(
Δ % BA or higher	**−5.898**	**−0.800**	**−6.697**	**−6.154**	*−0.275*	**−6.429**	**2.198**	**0.110**	**2.308**	**−10.865**	−0.225	**−11.089**	−5
Δ % Owner occupied	**−1.603**	**−0.217**	**−1.820**	**−2.780**	*−0.124*	**−2.904**	**0.842**	*0.042*	**0.884**	**−2.394**	−0.049	**−2.443**	−1
Neighborhood classifications													
Gentrification	**−0.380**	**−0.052**	**−0.431**	−0.003	0.000	−0.003	*−0.121*	−0.006	*−0.127*	*−0.220*	−0.005	*−0.225*	−(
Baseline neighborhood controls													
Density (in 1,000s)	**0.002**	0.000	**0.003**	**−0.016**	**−0.001**	**−0.016**	**0.008**	0.000	**0.009**	**−0.007**	0.000	**−0.008**	−(
Population	0.000	0.000	0.000	0.000	0.000	0.000	*0.000*	0.000	*0.000*	0.000	0.000	0.000	(

	Insufficient sleep			Obesity			Binge drinking			Smoking			
	Direct	**Indirect**	**Total**	**Direct**	**Indirect**	**Total**	**Direct**	**Indirect**	**Total**	**Direct**	**Indirect**	**Total**	**D**
% Non-Flispanic White	**−2.838**	**−0.385**	**−3.223**	**1.505**	0.067	**1.572**	**0.806**	0.040	**0.846**	**−1.760**	−0.036	**−1.796**	**0**
% Non-Hispanic Black	**0.509**	**0.069**	**0.578**	**3.424**	*0.153*	**3.577**	−0.100	−0.005	−0.105	**−3.131**	−0.065	**−3.196**	−0
% Hispanic	**−2.941**	**−0.399**	**−3.339**	**1.335**	0.060	**1.395**	**1.619**	0.081	**1.699**	**−3.979**	−0.082	**−4.062**	−0
% Foreign born	**−1.862**	**−0.253**	**−2.115**	**−0.884**	−0.039	**−0.923**	**−0.588**	−0.029	**−0.618**	**−1.511**	−0.031	**−1.542**	−1
% 18 years and under	**4.332**	**0.588**	**4.919**	**4.655**	*0.208*	**4.863**	**1.718**	0.086	**1.803**	**6.191**	0.128	**6.319**	3
Median home value (in 10,000s)	**0.009**	**0.001**	**0.010**	**−0.023**	*−0.001*	**−0.024**	**0.016**	0.001	**0.017**	**−0.023**	0.000	**−0.024**	−0
% BA or higher	**−4.022**	**−0.545**	**−4.568**	**−5.221**	*−0.233*	**−5.453**	**2.075**	0.103	**2.178**	**−8.362**	−0.173	**−8.535**	−2
% Owner occupied	**−1.391**	**−0.189**	**−1.580**	**−1.370**	*−0.061*	**−1.431**	**−0.355**	−0.018	**−0.373**	**−2.573**	−0.053	**−2.626**	−2
Baseline neighborhood health													
Insufficient sleep	**−0.410**	**−0.056**	**−0.465**										
Obesity				**−0.367**	*−0.016*	**−0.384**							
Binge drinking							**−0.195**	**−0.010**	**−0.204**				
Smoking										**−0.431**	−0.009	**−0.440**	
Poor mental health													−(

Note. Direct, indirect, and total effects are drawn from the baseline spatial autoregressive (SAR) models in Table 2. Bold indicates statistical significance at the 95% level or higher. Bolds indicate trend-level significance ($p < .10$). Models are performed without MSA fixed effects.

Table A2.

Pairwise correlation matrix for baseline neighborhood characteristics and neighborhood change measures.

	Δ % Non-Hispanic White	**Δ % Foreign born**	**Δ Median home value**	**Δ % Bachelor's degree or higher**	**Δ % Owner occupied**	**Density**	**Population**	**% Non-Hispanic White**	**% Non-Hispanic Black**	**% Hispanic**	**% Foreign born**
Δ % Non-Hispanic White	1.000										
Δ % Foreign born	−0.219	1.000									
Δ Median home value	0.097	−0.084	1.000								
Δ % Bachelor's	0.166	−0.074	0.129	1.000							

	Δ % Non-Hispanic White	Δ % Foreign born	Δ Median home value	Δ % Bachelor's degree or higher	Δ % Owner occupied	Density	Population	% Non-Hispanic White	% Non-Hispanic Black	% Hispanic	% Foreign born
degree or higher											
Δ % Owner occupied	0.027	−0.016	−0.002	0.089	1.000						
Density	0.118	−0.064	0.196	0.058	−0.008	1.000					
Population	−0.056	0.031	−0.037	−0.045	0.001	0.027	1.000				
% Non-Hispanic White	−0.289	0.049	−0.023	0.026	0.005	−0.148	0.063	1.000			
% Non-Hispanic Black	0.149	0.078	−0.154	0.027	−0.024	0.036	−0.224	−0.472	1.000		
% Hispanic	0.083	−0.116	0.124	−0.048	0.026	−0.003	0.176	−0.367	−0.567	1.000	
% Foreign born	0.097	−0.215	0.232	−0.007	−0.013	0.402	0.037	−0.268	−0.377	0.451	1.000
% 18 years and under	0.031	0.049	−0.121	−0.116	0.047	−0.149	0.208	−0.404	−0.006	0.476	−0.004
Median home value	0.078	−0.049	0.350	0.080	−0.010	0.373	−0.133	0.005	−0.106	−0.034	0.449
% Bachelor's degree or higher	−0.031	0.018	0.099	−0.030	−0.031	0.139	−0.054	0.545	−0.088	−0.523	−0.037
% Owner occupied	−0.177	0.059	−0.138	−0.066	−0.076	−0.376	0.091	0.324	−0.135	−0.125	−0.199

Table A3.

Fully interacted spatial autoregressive models predicting change in neighborhood health in gentrifying versus nongentrifying areas (full model results).

	Δ Insufficient sleep		Δ Obesity		Δ Binge drinking		Δ Smoking		Δ Poor Mental health	
	Coef.	***SE***	**Coef.**	***SE***	**Coef.**	***SE***	**Coef.**	**SE**	**Coef.**	**SE**
Neighborhood change										
Δ % Non-Hispanic White	−0.973 *	(0.397)	−0.143	(0.623)	−0.299	(0.334)	−0.298	(0.563)	−0.398	(0.393)
Δ % Foreign born	−1.132 **	(0.378)	−0.607	(0.592)	−0.553 +	(0.317)	0.421	(0.534)	0.223	(0.374)
Δ Median home value (in 10,000s)	0.013 ***	(0.004)	−0.009	(0.006)	0.00790 *	(0.003)	−0.009 +	(0.005)	−0.012 **	(0.004)
Δ % Bachelor's degree or higher	−5.759 ***	(0.386)	−5.989 ***	(0.606)	2.248 ***	(0.325)	−10.470 ***	(0.546)	−5.741 ***	(0.383)

	Δ Insufficient sleep		Δ Obesity		Δ Binge drinking		Δ Smoking		Δ Poor Mental health	
	Coef.	***SE***	**Coef.**	***SE***	**Coef.**	***SE***	**Coef.**	**SE**	**Coef.**	**SE**
Δ % Owner occupied	−1.699***	(0.314)	−2.835***	(0.492)	0.864**	(0.263)	−2.549***	(0.444)	−1.800***	(0.310)
Neighborhood classifications										
Gentrification	−0.182	(0.115)	−0.0976	(0.180)	−0.0295	(0.097)	−0.183	(0.163)	−0.213+	(0.114)
Interactions										
Gentrification × Neighborhood change										
Δ % Non-Hispanic White	−1.588	(1.234)	−3.390+	(1.937)	1.269	(1.038)	−4.048*	(1.748)	−3.408**	(1.222)
Δ % Foreign born	−1.015	(1.360)	−2.095	(2.133)	0.209	(1.144)	−1.446	(1.924)	−2.393+	(1.346)
Δ Median home value (in 10,000s)	−0.0124*	(0.006)	0.011	(0.009)	−0.0054	(0.005)	0.00689	(0.008)	0.0126*	(0.006)
Δ % Bachelor's degree or higher	−1.178	(1.153)	−0.822	(1.808)	−0.747	(0.969)	−2.961+	(1.632)	−0.873	(1.141)
Δ % Owner occupied	1.343	(1.179)	1.147	(1.852)	−0.437	(0.992)	2.289	(1.670)	1.455	(1.169)
Baseline neighborhood controls										
Density (in 1,000s)	0.002*	(0.001)	−0.016***	(0.002)	0.008***	(0.001)	−0.007***	(0.001)	−0.006***	(0.001)
Population (in 1,000s)	−0.010	(0.009)	−0.009	(0.014)	0.014*	(0.007)	−0.019	(0.012)	0.005	(0.009)
% Non-Hispanic White	−2.783***	(0.219)	1 521***	(0.322)	0.810***	(0.177)	−1.719***	(0.284)	0.549**	(0.197)
% Non-Hispanic Black	0.529**	(0.191)	3.432***	(0.356)	−0.096	(0.156)	−3.094***	(0.273)	−0.210	(0.187)
% Hispanic	−2.884***	(0.187)	1.360***	(0.315)	1.614***	(0.157)	−3.930***	(0.256)	−0.145	(0.176)
% Foreign born	−1.833***	(0.185)	−0.887**	(0.282)	−0.588***	(0.150)	1 y***	(0.254)	−1.374***	(0.179)
% 18 years and under	4.286***	(0.340)	4.665***	(0.513)	1 712***	(0.272)	6.212***	(0.482)	3.874***	(0.335)
Median home value (in 1,000s)	0.009***	(0.002)	−0.023***	(0.004)	0.016***	(0.002)	−0.023***	(0.003)	−0.017***	(0.002)
% Bachelor's degree or higher	−3.982***	(0.220)	−5.185***	(0.340)	2.068***	(0.170)	−8.340***	(0.320)	−2.875***	(0.220)
% Owner occupied	−1.376***	(0.094)	−1.347***	(0.144)	−0.362***	(0.072)	−2.545***	(0.146)	−2.427***	(0.102)
Baseline neighborhood health										
Insufficient sleep	−0.404***	(0.011)								

	Δ Insufficient sleep		Δ Obesity		Δ Binge drinking		Δ Smoking		Δ Poor Mental health	
	Coef.	***SE***	**Coef.**	***SE***	**Coef.**	***SE***	**Coef.**	**SE**	**Coef.**	**SE**
Obesity			−0.366***	(0.011)						
Binge drinking					−0.195***	(0.007)				
Smoking							−0.430***	(0.011)		
Poor mental health									−0.367***	(0.012)
Spatial lag										
Δ Insufficient sleep	0.210***	(0.028)								
Δ Obesity			0.072*	(0.036)						
Δ Binge drinking					0.079**	(0.030)				
Δ Smoking							0.036	(0.030)		
Δ Poor mental health									0.115***	(0.032)
Includes MSA fixed effects	Yes		Yes		Yes		Yes		Yes	
Akaike information criterion (AIC)	14,950.75		19,297.95		13,641.77		18,962.24		15409.86	

Note. N = 5039 tracts representing the 10 most populous metropolitan statistical areas (in 2000). Models include MSA fixed effects (constant suppressed). AIC was calculated via maximum likelihood estimation. See Appendix Table 3A for full model results that include baseline neighborhood health.

$^{+}$ p <.10.

* p < .05.

** p < .01.

*** p < .001.

Table A4.

Full results for cross-sectional SAR models interacting gentrification and initially majority Black

	Δ Insufficient sleep		Δ Obesity		Δ Binge drinking		Δ Smoking		Δ Poor mental health	
	Coef.	***SE***	**Coef.**	***SE***	**Coef.**	***SE***	**Coef.**	***SE***	**Coef.**	***SE***
Neighborhood change										
Δ % Non-Hispanic White	−1.116**	0.383	−0.503	0.597	−0.161	0.320	−0.684	0.539	−0.743*	0.377
Δ % Foreign born	−1.191**	0.368	−0.742	0.573	−0.541^{+}	0.307	0.326	0.517	0.051	0.362
Δ Median home value	0.008**	0.003	−0.005	0.005	0.006*	0.003	−0.007	0.004	−0.007*	0.003

	Δ Insufficient sleep		Δ Obesity		Δ Binge drinking		Δ Smoking		Δ Poor mental health	
	Coef.	***SE***	**Coef.**	***SE***	**Coef.**	***SE***	**Coef.**	***SE***	**Coef.**	***SE***
Δ % Bachelor's degree or higher	−5.863***	0.369	−6.146***	0.575	2 222***	0.308	−10.800***	0.518	−5.884***	0.364
Δ % Owner occupied	−1.593***	0.305	−2.790***	0.475	0.848***	0.254	−2.376***	0.429	−1.724***	0.300
Neighborhood classifications										
Gentrification	−0.353***	0.089	0.03	0.138	−0.084	0.074	−0.117	0.124	−0.053	0.087
Majority Black	−0.008	0.090	0.232+	0.140	−0.047	0.074	−0.095	0.126	0.040	0.088
Interactions										
Gentrification × Neighborhood type										
Majority Black	−0.103	0.151	−0.184	0.235	−0.139	0.126	−0.405+	0.212	−0.189	0.148
Baseline neighborhood characteristics										
Density (in 1,000s)	0.002*	0.001	−0.016***	0.002	0.008***	0.001	−0.007***	0.001	−0.006***	0.001
Population (in 1,000s)	−0.009	0.009	−0.007	0.014	0.014+	0.007	−0.019	0.012	0.006	0.009
% Non-Hispanic White	−2.819***	0.222	1.508***	0.322	0.820***	0.177	−1.738***	0.284	0.537**	0.198
% Non-Hispanic Black	0.531*	0.222	3.186***	0.389	−0.020	0.184	−2.963***	0.315	−0.246	0.218
% Hispanic	−2.919***	0.189	1.365***	0.316	1.632***	0.157	−3.949***	0.256	−0.156	0.177
% Foreign born	−1.853***	0.186	−0.902**	0.282	−0.586***	0.150	−1 512***	0.254	−1374***	0.179
% 18 years and under	4.312***	0.345	4744***	0.517	1.708***	0.273	6.168***	0.485	3.879***	0.337
Median home value (in 10,000s)	0.009***	0.002	−0.024***	0.004	0.016***	0.002	−0.023***	0.003	−0.017***	0.002
% Bachelor's degree or higher	−3.999***	0.222	−5.202***	0.340	2.077***	0.170	−8.350***	0.320	−2.891***	0.220
% Owner occupied	−1.381***	0.095	−1.396***	0.145	−0347***	0.073	−2.550***	0.147	−2.453***	0.103
Baseline neighborhood health										
Insufficient sleep	−0.408***	0.011								
Obesity			−0.369***	0.011						
Binge drinking					−0.195***	0.007				
Smoking							−0.431***	0.011		
Poor mental health									−0.368***	0.012

	Δ Insufficient sleep		Δ Obesity		Δ Binge drinking		Δ Smoking		Δ Poor mental health	
	Coef.	***SE***	**Coef.**	***SE***	**Coef.**	***SE***	**Coef.**	***SE***	**Coef.**	***SE***
Spatial lag										
Δ Insufficient sleep	0.184 ***	0.029								
Δ Obesity			0.070 $^{+}$	0.036						
Δ Binge drinking					0.076 *	0.030				
Δ Smoking							0.028	0.030		
Δ Poor mental health									0.114 ***	0.032
Includes MSA fixed effects	Yes		Yes		Yes		Yes		Yes	
Akaike information criterion (AIC)	14,953.79		19,292.04		13,636.24		18,962.94		15,416.82	

Note. The results correspond with Table 4 in the main text. $N = 5039$ tracts representing the 10 most populous metropolitan statistical areas (in 2000). Neighborhood majority racial composition was derived from 2000 decennial census tract data. Models include MSA fixed effects (constant suppressed). AIC was calculated via maximum likelihood estimation.

$^{+}p < .10.$

$^{*}p < .05.$

$^{**}p < .01.$

$^{***}p < .001.$

Table A5.

Full results for cross-sectional SAR models interacting gentrification and initially majority Hispanic.

	Δ Insufficient sleep		Δ Obesity		Δ Binge drinking		Δ Smoking		Δ Poor mental health	
	Coef.	***SE***	**Coef.**	***SE***	**Coef.**	***SE***	**Coef.**	***SE***	**Coef.**	***SE***
Neighborhood change										
Δ % Non-Hispanic White	−1.100 **	0.384	−0.549	0.594	−0.194	0.320	−0.689	0.539	−0.707 $^{+}$	0.377
Δ % Foreign born	−1.186 **	0.369	−0.795	0.570	−0.523 $^{+}$	0.307	0.342	0.517	0.058	0.362
Δ Median home value	0.008 **	0.003	−0.006	0.005	0.005 *	0.003	−0.006	0.004	−0.007 *	0.003
Δ % Bachelor's degree or higher	−5.887 ***	0.369	−6.143 ***	0.571	2.214 ***	0.308	−10.881 ***	0.517	−5.933 ***	0.363
Δ % Owner occupied	−1.623 ***	0.306	−2.724 ***	0.472	0.849 ***	0.254	−2.428 ***	0.429	−1.765 ***	0.300
Neighborhood classifications										

	Δ Insufficient sleep		Δ Obesity		Δ Binge drinking		Δ Smoking		Δ Poor mental health	
	Coef.	***SE***	**Coef.**	***SE***	**Coef.**	***SE***	**Coef.**	***SE***	**Coef.**	***SE***
Gentrification	−0.370***	0.088	0.030	0.136	−0.182*	0.073	−0.166	0.123	−0.039	0.086
Majority Hispanic	−0.091	0.059	0.255**	0.092	−0.015	0.049	−0.106	0.083	−0.135*	0.059
Interactions										
Gentrification × Neighborhood type										
Majority Hispanic	−0.054	0.150	−0.099	0.232	0.274*	0.125	−0.256	0.211	−0.285+	0.147
Baseline neighborhood characteristics										
Density (in 1,000s)	0.003*	0.001	−0.016***	0.002	0.008***	0.001	−0.007***	0.001	−0.006***	0.001
Population (in 1,000s)	−0.010	0.009	−0.007	0.014	0.014+	0.007	−0.019	0.012	0.005	0.009
% Non-Hispanic White	−2.820***	0.221	1.488***	0.320	0.808***	0.177	−1.739***	0.284	0.553**	0.198
% Non-Hispanic Black	0.537**	0.194	3.407***	0.355	−0.097	0.157	−3.091 ***	0.275	−0.181	0.188
% Hispanic	−2.791***	0.208	1.004**	0.338	1.620***	0.176	−3.790***	0.285	0.059	0.196
% Foreign born	−1.849***	0.187	−0.932***	0.281	−0.577***	0.150	−1.501***	0.255	−1.365***	0.179
% 18 years and under	4.293***	0.344	4.722***	0.512	1.738***	0.272	6.133***	0.483	3.776***	0.336
Median home value (in 10,000s)	0.009***	0.002	−0.024***	0.004	0.016***	0.002	−0.023***	0.003	−0.016***	0.002
% Bachelor’s degree or higher	−4.013***	0.222	5 232***	0.339	2.088***	0.170	−8.361***	0.320	−2.888***	0.220
% Owner occupied	−1.403***	0.095	−1.347***	0.144	−0.351***	0.073	−2.592***	0.147	−2.470***	0.102
Baseline neighborhood health										
Insufficient sleep	−0.409***	0.011								
Obesity			−0.368***	0.011						
Binge drinking					−0.195***	0.007				
Smoking							−0.431 ***	0.011		
Poor mental health									−0.366***	0.012
Spatial lag										
Δ Insufficient sleep	0.178***	0.029								
Δ Obesity			0.088*	0.035						
Δ Binge drinking					0.073*	0.030				

	Δ Insufficient sleep		Δ Obesity		Δ Binge drinking		Δ Smoking		Δ Poor mental health	
	Coef.	***SE***	**Coef.**	***SE***	**Coef.**	***SE***	**Coef.**	***SE***	**Coef.**	***SE***
Δ Smoking							0.032	0.030		
Δ Poor mental health									0.107***	0.033
Includes MSA fixed effects	Yes		Yes		Yes		Yes		Yes	
Akaike information criterion (AIC)	14,955.02		19,286.43		13,633.29		18,963.63		15,410.71	

Note. The results correspond with Table 5 in the main text. $N = 5039$ tracts representing the 10 most populous metropolitan statistical areas (in 2000). Neighborhood majority racial composition was derived from 2000 decennial census tract data. Models include MSA fixed effects (constant suppressed). AIC was calculated via maximum likelihood estimation.

+ $p < .10$.

* $p < .05$.

** $p < .01$.

*** $p < .001$.

Table A6.

Full results for cross-sectional SAR models interacting gentrification and initially majority White.

	Δ Insufficient sleep		Δ Obesity		Δ Binge drinking		Δ Smoking		Δ Poor mental health	
	Coef.	***SE***	**Coef.**	***SE***	**Coef.**	***SE***	**Coef.**	***SE***	**Coef.**	***SE***
Neighborhood change										
Δ % Non-Hispanic White	−1.045**	0.384	−0.34	0.597	−0.14	0.321	−0.656	0.541	−0.675+	0.377
Δ % Foreign born	−1.183**	0.368	−0.717	0.572	−0.512+	0.307	0.344	0.517	0.052	0.362
Δ Median home value	0.008**	0.003	−0.006	0.005	0.006*	0.003	−0.007	0.004	−0.007*	0.003
Δ % Bachelor's degree or higher	−5.900***	0.369	−6.189***	0.573	2.189***	0.308	−10.886***	0.518	−5.935***	0.363
Δ % Owner occupied	−1.580***	0.305	−2.750***	0.474	0.846***	0.254	2 377***	0.429	−1.705***	0.300
Neighborhood classifications										
Gentrification	−0.408***	0.089	0.010	0.138	−0.084	0.074	−0.253*	0.125	−0.144+	0.087
Majority White	−0.209**	0.073	−0.378***	0.113	−0.097	0.060	−0.191+	0.102	−0.212**	0.071
Interactions										
Gentrification × Neighborhood type										

	Δ Insufficient sleep		Δ Obesity		Δ Binge drinking		Δ Smoking		Δ Poor mental health	
	Coef.	***SE***	**Coef.**	***SE***	**Coef.**	***SE***	**Coef.**	***SE***	**Coef.**	***SE***
Majority White	0.125	0.171	−0.095	0.267	−0.184	0.143	0.140	0.241	0.206	0.168
Baseline neighborhood characteristics										
Density (in 1,000s)	0.002*	0.001	−0.016***	0.002	0.008***	0.001	−0.007***	0.001	−0.006***	0.001
Population (in 1,000s)	−0.009	0.009	−0.009	0.014	0.014+	0.007	−0.019	0.012	0.006	0.009
% Non-Hispanic White	−2.590***	0.236	2.024***	0.353	0.954***	0.193	−1.524***	0.313	0.786***	0.218
% Non-Hispanic Black	0.530**	0.193	3.491 ***	0.356	−0.086	0.156	2.117***	0.274	−0.206	0.187
% Hispanic	−2.956***	0.188	1344***	0.315	1.615***	0.157	−3.992***	0.256	−0.179	0.176
% Foreign born	−1.867***	0.187	−0.906**	0.282	−0.586***	0.150	−1.529***	0.255	−1.394***	0.179
% 18 years and under	4383***	0.344	4.753***	0.514	1 751***	0.272	6.246***	0.484	3.909***	0.336
Median home value (in 10,000s)	0.009***	0.002	−0.023***	0.004	0.016***	0.002	−0.023***	0.003	−0.017***	0.002
% Bachelor's degree or higher	−4.131***	0.226	−5.411***	0.346	2.024***	0.172	−8.475***	0.326	−3.017***	0.224
% Owner occupied	−1.363***	0.095	1.213***	0.145	−0.336***	0.073	−2.554***	0.146	−2.429***	0.103
Baseline neighborhood health										
Insufficient sleep	−0.411***	0.011								
Obesity			−0.368***	0.011						
Binge drinking					−0.195***	0.007				
Smoking							−0.432***	0.011		
Poor mental health									−0.369***	0.012
Spatial lag										
Δ Insufficient sleep	0.183***	0.029								
Δ Obesity			0.073*	0.036						
Δ Binge drinking					0.072*	0.030				
Δ Smoking							0.031	0.030		
Δ Poor mental health									0.112***	0.032
Includes MSA fixed effects	Yes		Yes		Yes		Yes		Yes	

	Δ Insufficient sleep		Δ Obesity		Δ Binge drinking		Δ Smoking		Δ Poor mental health	
	Coef.	***SE***	**Coef.**	***SE***	**Coef.**	***SE***	**Coef.**	***SE***	**Coef.**	***SE***
Akaike information criterion (AIC)	14,949.35		19,292.75		13,634.19		18,963.62		15,411.56	

Note. Results correspond with Table 6 in the main text. $N = 5039$ tracts representing the 10 most populous metropolitan statistical areas (in 2000). Neighborhood majority racial composition was derived from 2000 decennial census tract data. Models include MSA fixed effects (constant suppressed). AIC was calculated via maximum likelihood estimation.

+ $p < .10$.

* $p < .05$.

** $p < .01$.

*** $p < .001$.

Table A7.

Summary of tables.

	Table summary	Associated questions
Table 1	Descriptive statistics for our dependent variables, key predictors, and related measures; global Moran's I values for baseline health prevalence measures and DVs (i.e., change in neighborhood health prevalence rates from 2013–2018)	What is the sample overview? Is there evidence of spatial autocorrelation in: (a) baseline neighborhood health; and (b) change in prevalence of neighborhood health outcomes, status, and risk behavior?
Table 2	Spatial autoregressive (SAR) model (w/spatial lag on DV (SLDV)) examining the association between components of neighborhood change and change in neighborhood health conditional on gentrification	Does neighborhood health change as neighborhood sociodemographics change?
Table 3	SAR model (SLDV) examining the interaction between neighborhood change and gentrification on changes in neighborhood health	(a) Does change in neighborhood health occur differently in neighborhoods experiencing gentrification relative to those that are not?; (b) Which types of sociodemographic change are associated with changing neighborhood health in gentrifying neighborhoods?
Tables 4–6	SAR model (SLDV) examining the interaction between gentrification and initial neighborhood racial composition on changes in neighborhood health in:	Do these changes to neighborhood health depend on the initial racial composition of the neighborhood?
Table 4	Initially majority (>50%) Black neighborhoods	
Table 5	Initially majority (>50%) Hispanic neighborhoods	
Table 6	Initially majority (>70%) White neighborhoods	

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Table 1.

Tract-level descriptive statistics of outcomes, covariates, and related measures for analytic sample (10 MSAs, 5039 tracts).

	Mean	*SD*
Baseline neighborhood factors		
Density	18,862	22,705
Population	4,446	2,048
% non-Hispanic White	23.67	24.12
% non-Hispanic Black	25.51	30.58
% Hispanic	41.10	28.29
% Foreign born	28.57	16.23
% 18 years and under	24.72	7.01
Median home value	249,113	140,506
% BA or higher	21.27	14.14
% owner occupied	42.16	21.88
Change in neighborhood factors, 2010–14 to 2015–19		
Change in % non-Hispanic White	−0.54	4.65
Change in % non-Hispanic Black	−0.54	4.61
Change in % Hispanic	0.69	5.72
Change in % foreign born	0.00	4.67
Change in median home value	60,608	68,385
Change in % BA or higher	1.81	4.63
Change in owner occupied	0.71	5.26
Neighborhood classifications		
% Gentrified	6.6	
% Majority Black	22.9	
% Majority Hispanic	29.2	
% Majority White	15.4	

	Mean	SD	Moran's I	p value
Baseline and change in neighborhood health				
Insufficient sleep	40.36	5.08	0.846	0.000
Change in insufficient sleep	−0.93	1.61	0.815	0.000
Obesity	31.65	6.63	0.840	0.000
Change in obesity	−0.13	2.09	0.634	0.000
Binge drinking	15.75	2.89	0.735	0.000
Change in binge drinking	1.84	1.00	0.615	0.000
Smoking	19.67	4.92	0.746	0.000
Change in smoking	−1.24	1.88	0.384	0.000
Poor mental health	13.88	3.04	0.749	0.000
Change in poor mental health	0.70	1.39	0.494	0.000

Note. The analytical sample is restricted to tracts with full data that were eligible to gentrify. BA refers to bachelor's degree. Baseline and change in neighborhood health measured are derived from CDC-Places data at the tract level via small-area estimation; Moran's I is computed using a queen's first-order weights matrix and under the null hypothesis of spatial randomization. Baseline neighborhood measures were lagged by 1 year and drawn from American Community Survey (ACS) 2010–14 estimates. We observe change in neighborhood health from 2013–14 to 2017–18. Neighborhood change is calculated using the ACS, 2010–14 and 2015–19. Majority racial composition is drawn from 2000 decennial census population counts. See Appendix Table A2 for pairwise correlations for all baseline neighborhood measures and neighborhood change variables.

Table 2.

Spatial autoregressive models predicting change in neighborhood health conditional on gentrification and sociodemographic change.

	Δ Insufficient sleep		Δ Obesity		Δ Binge drinking		Δ Smoking		Δ Poor mental health	
	Coef.	***SE***	**Coef.**	***SE***	**Coef.**	***SE***	**Coef.**	***SE***	**Coef.**	***SE***
Neighborhood change										
Δ % non-Hispanic White	−1.127**	(0.383)	−0.497	(0.597)	−0.182	(0.320)	−0.733	(0.539)	−0.757*	(0.377)
Δ % Foreign born	−1.190**	(0.368)	−0.753	(0.574)	−0.536+	(0.307)	0.342	(0.517)	0.053	(0.362)
Δ Median home value (in 10,000s)	0.008**	(0.003)	−0.005	(0.005)	0.006*	(0.003)	−0.007+	(0.004)	−0.007*	(0.003)
Δ % BA or higher	—5.879***	(0.369)	−6.152***	(0.575)	2.197***	(0.308)	−10.860***	(0.518)	—5.910***	(0.364)
Δ % Owner occupied	— 1.598***	(0.305)	—2.779***	(0.475)	0.842***	(0.254)	—2.394***	(0.429)	−1.726***	(0.300)
Neighborhood classifications										
Gentrification	—0.379***	(0.081)	−0.00278	(0.126)	−0.121+	(0.068)	−0.220+	(0.114)	−0.0969	(0.080)
Baseline neighborhood context										
Density (in 1,000s)	0.002*	(0.001)	−0.016***	(0.002)	0.008***	(0.001)	−0.008***	(0.001)	−0.006***	(0.001)
Population (in 1,000s)	−0.009	(0.009)	−0.008	(0.014)	0.014+	(0.007)	−0.019	(0.012)	0.006	(0.009)
% non-Hispanic White	−2.830***	(0.221)	1504***	(0.322)	0.805***	(0.177)	−1.760***	(0.284)	0.532**	(0.198)
% non-Hispanic Black	0.508**	(0.193)	3.423***	(0.357)	−0.100	(0.156)	—3131***	(0.274)	−0.219	(0.188)
% Hispanic	—2.932***	(0.188)	1 335***	(0.316)	1.618***	(0.157)	—3.979***	(0.256)	−0.168	(0.177)
% Foreign born	−1.856***	(0.187)	−0.883**	(0.282)	−0.588***	(0.150)	—1 511***	(0.254)	— 1.374***	(0.179)
% 18 years and under	4.319***	(0.343)	4.654***	(0.515)	1717***	(0.272)	6.190***	(0.483)	3.861***	(0.335)
Median home value (in 10,000s)	0.009***	(0.002)	−0.023***	(0.004)	0.016***	(0.002)	−0.023***	(0.003)	−0.017***	(0.002)
% BA or higher	−4.010***	(0.222)	—5.219***	(0.341)	2.074***	(0.170)	−8.361***	(0.320)	—2.905***	(0.220)
% Owner occupied	−1.387***	(0.094)	−1.369***	(0.144)	−0.355***	(0.072)	—2 573***	(0.146)	—2.454***	(0.102)
Baseline neighborhood health										
Insufficient sleep	−0.408***	(0.011)								
Obesity			−0.367***	(0.011)						
Binge drinking					—0.194***	(0.007)				

	Δ Insufficient sleep		Δ Obesity		Δ Binge drinking		Δ Smoking		Δ Poor mental health	
	Coef.	***SE***	**Coef.**	***SE***	**Coef.**	***SE***	**Coef.**	***SE***	**Coef.**	***SE***
Smoking							—0.431***	(0.011)		
Poor mental health									−0.368***	(0.012)
Spatial lag										
Δ Sleep	0.182***	(0.029)								
Δ Obesity			0.065+	(0.036)						
Δ Binge drinking					0.072*	(0.030)				
Δ Smoking							0.031	(0.030)		
Δ Mental health									0.110***	(0.033)
Includes MSA fixed effects	Yes		Yes		Yes		Yes		Yes	
Akaike information criterion (AIC)	14,951.74		19,293.66		13,634.4		18,963.17		15,415.05	14,951.74

Note. N = 5039 tracts representing the 10 most populous metropolitan statistical areas (MSAs) (in 2000). The dependent variables capture the change in the prevalence of each health dimension from 2013 to 2018. BA refers to bachelor's degree. Models include MSA fixed effects (constant suppressed). AIC is calculated via maximum likelihood estimation.

+ $p < .10$.

* $p < .05$.

** $p < .01$.

*** $p < .001$.

Table 3.

Spatial autoregressive models predicting change in neighborhood health in gentrifying versus nongentrifying areas.

	Δ Insufficient sleep		Δ Obesity		Δ Binge drinking		Δ Smoking		Δ Poor mental health	
	Coef.	***SE***	**Coef.**	***SE***	**Coef.**	***SE***	**Coef.**	***SE***	**Coef.**	***SE***
Neighborhood change										
Δ % non-Hispanic White	−0.973*	(0.397)	−0.143	(0.623)	−0.299	(0.334)	−0.298	(0.563)	−0.398	(0.393)
Δ % Foreign born	−1.132**	(0.378)	−0.607	(0.592)	−0.553^{+}	(0.317)	0.421	(0.534)	0.223	(0.374)
Δ Median home value (in 10,000s)	0.013***	(0.004)	−0.009	(0.006)	0.00790*	(0.003)	−0.009^{+}	(0.005)	−0.012**	(0.004)
Δ % BA or higher	−5.759***	(0.386)	−5.989***	(0.606)	2.248***	(0.325)	−10.470***	(0.546)	−5.741***	(0.383)
Δ % Owner occupied	− 1.699***	(0.314)	−2.835***	(0.492)	0.864**	(0.263)	−2.549***	(0.444)	−1.800***	(0.310)
Neighborhood classifications										
Gentrification	−0.182	(0.115)	−0.0976	(0.180)	−0.0295	(0.097)	−0.183	(0.163)	−0.213^{+}	(0.114)
Interactions										
Gentrification × Neighborhood change										
Δ % non-Hispanic White	−1.588	(1.234)	−3.390^{+}	(1.937)	1.269	(1.038)	−4.048*	(1.748)	−3.408**	(1.222)
Δ % Foreign born	−1.015	(1.360)	−2.095	(2.133)	0.209	(1.144)	−1.446	(1.924)	−2.393^{+}	(1.346)
Δ Median home value (in 10,000s)	−0.0124*	(0.006)	0.011	(0.009)	−0.0054	(0.005)	0.00689	(0.008)	0.0126*	(0.006)
Δ % BA or higher	−1.178	(1.153)	−0.822	(1.808)	−0.747	(0.969)	−2.961^{+}	(1.632)	−0.873	(1.141)
Δ % Owner occupied	1.343	(1.179)	1.147	(1.852)	−0.437	(0.992)	2.289	(1.670)	1.455	(1.169)
Baseline neighborhood controls										
Density (in 1,000s)	0.002*	(0.001)	−0.016***	(0.002)	0.008***	(0.001)	−0.007***	(0.001)	−0.006***	(0.001)
Population (in 1,000s)	−0.010	(0.009)	−0.009	(0.014)	0.014*	(0.007)	−0.019	(0.012)	0.005	(0.009)
% Non-Hispanic White	−2.783***	(0.219)	1 521***	(0.322)	0.810***	(0.177)	− 1.719***	(0.284)	0.549**	(0.197)
% Non-Hispanic Black	0.529**	(0.191)	3.432***	(0.356)	−0.096	(0.156)	−3.094***	(0.273)	−0.210	(0.187)
% Hispanic	−2.884***	(0.187)	1.360***	(0.315)	1.614***	(0.157)	−3.930***	(0.256)	−0.145	(0.176)
% Foreign born	−1.833***	(0.185)	−0.887**	(0.282)	−0.588***	(0.150)	1 517***	(0.254)	− 1.374***	(0.179)
% 18 years and under	4.286***	(0.340)	4.665***	(0.513)	1 712***	(0.272)	6.212***	(0.482)	3.874***	(0.335)

	Δ Insufficient sleep		Δ Obesity		Δ Binge drinking		Δ Smoking		Δ Poor mental health	
	Coef.	*SE*	Coef.	*SE*	Coef.	*SE*	Coef.	*SE*	Coef.	*SE*
Median home value (in 1,000s)	0.009***	(0.002)	−0.023***	(0.004)	0.016***	(0.002)	−0.023***	(0.003)	−0.017***	(0.002)
% BA or higher	−3.982***	(0.220)	−5.185***	(0.340)	2.068***	(0.170)	−8.340***	(0.320)	−2.875***	(0.220)
% Owner occupied	−1.376***	(0.094)	− 1.347***	(0.144)	−0.362***	(0.072)	−2.545***	(0.146)	−2.427***	(0.102)
Spatial lag										
Δ Insufficient sleep	0.210***	(0.028)								
Δ Obesity			0.072*	(0.036)						
Δ Binge drinking					0.079**	(0.030)				
Δ Smoking							0.036	(0.030)		
Δ Poor mental health									0.115***	(0.032)
Includes MSA fixed effects	Yes		Yes		Yes		Yes		Yes	
Akaike information criterion (AIC)	14,950.75		19,297.95		13,641.77		18,962.24		15,409.86	

Note. N = 5039 tracts representing the 10 most populous metropolitan statistical areas (MSAs) (in 2000). The dependent variables capture the change in the prevalence of each health dimension from 2013 to 2018. BA refers to bachelor's degree. Models include MSA fixed effects (constant suppressed). AIC is calculated via maximum likelihood estimation. See Appendix Table A3 for full model results that include baseline neighborhood health.

+ $p < .10$.

* $p < .05$.

** $p < .01$.

*** $p < .001$.

Table 4.

SAR models predicting change in neighborhood health in gentrifying and nongentrifying neighborhoods (by majority Black).

	Δ Insufficient Sleep		Δ Obesity		Δ Binge drinking		Δ Smoking		Δ Poor mental health	
	Coef.	***SE***	**Coef.**	***SE***	**Coef.**	***SE***	**Coef.**	***SE***	**Coef.**	***SE***
Neighborhood change										
Δ % non-Hispanic White	-1.116^{**}	0.383	−0.503	0.597	−0.161	0.320	−0.684	0.539	-0.743^{*}	0.377
Δ % Foreign born	-1.191^{**}	0.368	−0.742	0.573	-0.541^{+}	0.307	0.326	0.517	0.051	0.362
Δ Median home value	0.008^{**}	0.003	−0.005	0.005	0.006^{*}	0.003	−0.007	0.004	-0.007^{*}	0.003
Δ % BA or higher	-5.863^{***}	0.369	-6.146^{***}	0.575	$2\ 222^{***}$	0.308	-10.800^{***}	0.518	-5.884^{***}	0.364
Δ % Owner occupied	-1.593^{***}	0.305	-2.790^{***}	0.475	0.848^{***}	0.254	-2.376^{***}	0.429	-1.724^{***}	0.300
Neighborhood classifications										
Gentrification	-0.353^{***}	0.089	0.03	0.138	−0.084	0.074	−0.117	0.124	−0.053	0.087
Majority Black	−0.008	0.090	0.232^{+}	0.140	−0.047	0.074	−0.095	0.126	0.040	0.088
Interactions										
Gentrification × Neighborhood type										
Majority Black	−0.103	0.151	−0.184	0.235	−0.139	0.126	-0.405^{+}	0.212	−0.189	0.148
Spatial lag										
Δ Insufficient sleep	0.184^{***}	0.029								
Δ Obesity			0.070^{+}	0.036						
Δ Binge drinking					0.076^{*}	0.030				
Δ Smoking							0.028	0.030		
Δ Poor mental health									0.114^{***}	0.032
Includes MSA fixed effects	Yes		Yes		Yes		Yes		Yes	
Includes baseline neighborhood factors	Yes		Yes		Yes		Yes		Yes	
Includes baseline neighborhood health	Yes		Yes		Yes		Yes		Yes	
Akaike information criterion (AIC)	14,953.79		19,292.04		13,636.24		18,962.94		15,416.82	

Note. N = 5039 tracts representing the 10 most populous metropolitan statistical areas (MSAs) (in 2000). Neighborhood majority racial composition was derived from 2000 decennial census tract data. BA refers to bachelor's degree. The dependent variables capture the change in the prevalence of each health dimension from 2013 to 2018. Models include MSA fixed effects (constant suppressed). AIC was calculated via maximum likelihood estimation. See Appendix Table A4 for full model results that include coefficients for baseline neighborhood characteristics and baseline neighborhood health.

+ $p < .10$.

* $p < .05$.

** $p < .01$.

*** $p < .001$.

Table 5 .

SAR models predicting change in neighborhood health in gentrifying and nongentrifying neighborhoods (by majority Hispanic).

	Δ Insufficient sleep		Δ Obesity		Δ Binge drinking		Δ Smoking		Δ Poor mental health	
	Coef.	***SE***	**Coef.**	***SE***	**Coef.**	***SE***	**Coef.**	***SE***	**Coef.**	***SE***
Neighborhood change										
Δ % Non-Hispanic White	−1.100**	0.384	−0.549	0.594	−0.194	0.320	−0.689	0.539	−0.707+	0.377
Δ % Foreign born	−1.186**	0.369	−0.795	0.570	−0.523+	0.307	0.342	0.517	0.058	0.362
Δ Median home value	0.008**	0.003	−0.006	0.005	0.005*	0.003	−0.006	0.004	−0.007*	0.003
Δ % BA or higher	−5.887***	0.369	−6.143***	0.571	2.214***	0.308	−10.881***	0.517	−5.933***	0.363
Δ % Owner occupied	−1.623***	0.306	−2.724***	0.472	0.849***	0.254	−2.428***	0.429	−1.765***	0.300
Neighborhood classifications										
Gentrification	−0.370***	0.088	0.030	0.136	−0.182*	0.073	−0.166	0.123	−0.039	0.086
Majority Hispanic	−0.091	0.059	0.255**	0.092	−0.015	0.049	−0.106	0.083	−0.135*	0.059
Interactions										
Gentrification × Neighborhood type										
Majority Hispanic	−0.054	0.150	−0.099	0.232	0.274*	0.125	−0.256	0.211	−0.285+	0.147
Spatial lag										
Δ Insufficient sleep	0.178***	0.029								
Δ Obesity			0.088*	0.035						
Δ Binge drinking					0.073*	0.030				
Δ Smoking							0.032	0.030		
Δ Poor mental health									0.107***	0.033
Includes MSA fixed effects	Yes		Yes		Yes		Yes		Yes	
Includes baseline neighborhood factors	Yes		Yes		Yes		Yes		Yes	
Includes baseline neighborhood health	Yes		Yes		Yes		Yes		Yes	
Akaike information criterion (AIC)	14,955.02		19,286.43		13,633.29		18,963.63		15,410.71	

Note. N = 5039 tracts representing the 10 most populous metropolitan statistical areas (MSAs) (in 2000). Neighborhood majority racial composition was derived from 2000 decennial census tract data. BA refers to bachelor's degree. The dependent variables capture the change in the prevalence of each health dimension from 2013 to 2018. Models include MSA fixed effects (constant suppressed). AIC was calculated via maximum likelihood estimation. See Appendix Table A5 for full model results that include coefficients for baseline neighborhood characteristics and baseline neighborhood health.

+ $p < .10$.

* $p < .05$.

** $p < .01$.

*** $p < .001$.

Table 6.

SAR models predicting change in neighborhood health in gentrifying and nongentrifying neighborhoods (by majority White).

	Δ Insufficient sleep		Δ Obesity		Δ Binge drinking		Δ Smoking		Δ Poor mental health	
	Coef.	***SE***	**Coef.**	***SE***	**Coef.**	***SE***	**Coef.**	***SE***	**Coef.**	***SE***
Neighborhood change										
Δ % Non-Hispanic White	−1.045**	0.384	−0.34	0.597	−0.14	0.321	−0.656	0.541	−0.675+	0.377
Δ % Foreign born	−1.183**	0.368	−0.717	0.572	−0.512+	0.307	0.344	0.517	0.052	0.362
Δ Median home value	0.008**	0.003	−0.006	0.005	0.006*	0.003	−0.007	0.004	−0.007*	0.003
Δ % BA or higher	−5.900***	0.369	−6.189***	0.573	2.189***	0.308	−10.886***	0.518	−5.935***	0.363
Δ % Owner occupied	−1.580***	0.305	−2.750***	0.474	0.846***	0.254	2 377***	0.429	−1.705***	0.300
Neighborhood classifications										
Gentrification	−0.408***	0.089	0.010	0.138	−0.084	0.074	−0.253*	0.125	−0.144+	0.087
Majority White	−0.209**	0.073	−0.378***	0.113	−0.097	0.060	−0.191 +	0.102	−0.212**	0.071
Interactions										
Gentrification × Neighborhood type										
Majority White	0.125	0.171	−0.095	0.267	−0.184	0.143	0.140	0.241	0.206	0.168
Spatial lag										
Δ Insufficient sleep	0.183***	0.029								
Δ Obesity			0.073*	0.036						
Δ Binge drinking					0.072*	0.030				
Δ Smoking							0.031	0.030		
Δ Poor mental health									0.112***	0.032
Includes MSA fixed effects	Yes		Yes		Yes		Yes		Yes	
Includes baseline neighborhood factors	Yes		Yes		Yes		Yes		Yes	
Includes baseline neighborhood health	Yes		Yes		Yes		Yes		Yes	
Akaike information criterion (AIC)	14949.35		19292.75		13634.19		18963.62		15411.56	

Note. N = 5039 tracts representing the 10 most populous metropolitan statistical areas (MSAs) (in 2000). Neighborhood majority racial composition was derived from 2000 decennial census tract data. BA refers to bachelor's degree. The dependent variables capture the change in the prevalence of each health dimension from 2013 to 2018. Models include MSA fixed effects (constant suppressed). AIC was calculated via maximum likelihood estimation. See Appendix Table A6 for full model results that include coefficients for baseline neighborhood characteristics and baseline neighborhood health.

+ $p < .10$.

* $p < .05$.

** $p < .01$.

*** $p < .001$.