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Impact of Gentrification on Adult Mental Health

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Impact of Gentrification on Adult Mental Health

A dissertation submitted in partial satisfaction of the

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in Health Policy and Management

by

Linda Diem Tran

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ABSTRACT OF THE DISSERTATION

Impact of Gentrification on Adult Mental Health

by

Linda Diem Tran

Doctor of Philosophy in Health Policy and Management

University of California, Los Angeles, 2018

Professor Ninez A Ponce, Chair

Gentrification is a dynamic process that changes the physical, economic, social, and cultural characteristics of historically underserved neighborhoods. This neighborhood transition process can improve the material and environmental circumstances of some residents and bring forth harmful consequences such as heightened financial stress and residential displacement for other community members. The subsequent impact of gentrification on population health is understudied, and little is known about how gentrification influences the mental wellness of residents.

This dissertation advances the small but growing literature on the relationship between gentrification and adult mental health. Using multiple data sources, we identified Southern California neighborhoods that gentrified between 2010 and 2015 and investigated the impact of living in a

gentrified neighborhood on mental health distress. Econometric techniques such as instrumental variables estimation and propensity score analyses were applied to reduce bias arising from residential selection and reverse causality.

The first study compared three quantitative approaches for identifying gentrified neighborhoods and demonstrated that each approach generated a different set of results. Findings highlighted the importance of the strategy used for identifying gentrified neighborhoods, especially when assessing gentrification's effects on health outcomes. The second study used five years of pooled data from the California Health Interview Survey to examine the causal relationship between gentrification and adult mental health. Relative to living in a low-income and not gentrified neighborhood, living in a gentrified neighborhood was associated with increased likelihood of serious psychological distress among longtime residents, renters, and people with low incomes. In the third study, we evaluated reasons for moving between residents who moved within gentrified and not gentrified neighborhoods and found evidence that people in gentrified neighborhoods were more likely to experience within-neighborhood displacement. Residents who experienced within-neighborhood displacement had greater likelihoods of having serious psychological distress.

Taken together, findings suggest that gentrification imposes a mental health cost on longtime residents and the most financially vulnerable residents, which has important implications for population health. By elevating levels of mental health distress of population groups who are already disproportionately exposed to stressors, gentrification can exacerbate mental health inequities.

The dissertation of Linda Diem Tran is approved.

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2018

To my parents and grandparents, whose unspoken dreams and unconditional support have guided me through this journey.

And to my love, Elokin Orton-Cheung. Your Taurus magic and fierce love have kept me grounded and nourished through these years.

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List of Acronyms

2SLS	Two-Stage Least Squares
ACS	American Community Survey
AME	Average Marginal Effect
API	Academic Performance Index
ATE	Average Treatment Effect
ATT	Average Treatment Effect of the Treated
BA/BS	Bachelor of Arts/Bachelor of Science
CEM	Coarsened Exact Matching
CATI	Computer-Assisted Telephone Interview
CHIS	California Health Interview Survey
DSM-IV	Diagnostic and Statistical Manual, 4^{th} Edition
FFIEC	Federal Financial Institutions Examination Council
FIPS	Federal Information Processing Standards
FPL	Federal Poverty Level
HMDA	Home Mortgage Disclosure Act
IRR	Incidence-Rate Ratio
MSA	Metropolitan Statistical Area
NCES	National Center for Education Statistics
PCA	Principal Components Analysis
SE	Standard Error
SES	Socioeconomic Status
SPD	Serious Psychological Distress

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I have deep gratitude for Dr. Ninez Ponce, my committee chair and mentor, whose guidance and steadfast support have made this dissertation possible. Thank you for smiling at my moments of doubt and nudging me forward. You embody the intellect, poise, and integrity to which I aspire. Dr. Thomas Rice, your research and career advice have been invaluable, and I am grateful to you for holding me and my work to the highest standards. Dr. Paul Ong, I am forever indebted to you for taking a chance on a graduate student looking for meaningful work over ten years ago. Thank you for your ribbing, which always expressed: "I expect the best work from you, and I know you can do it." I am also thankful for Dr. Sudipto Banerjee for offering his expertise and vast experience in biostatistics, Dr. Donatello Telesca for lending statistical confidence, and for Julia Liou for grounding the research in the perspectives of community members most affected by gentrification.

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I wish to express special thanks to my amazing family and friends. I have so much love and gratitude for my partner, my teammate, Elokin Orton-Cheung. From sending meals during comps to small but impactful gestures like taking Mochi on walks, you've supported me brilliantly from the start of this journey. I couldn't have been more lucky to have you on my side. Last but not least, to the pup with the kind heart and enigmatic stares, my companion, Mochi, I love you!

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Recent Research Experience

UCLA Center for Health Policy Research - Los Angeles, CA (2014-2018)
Graduate Student Researcher
Lead author in the development of policy briefs for the California Department of Health, Mental Health Services Division. These policy briefs use data from the California Health Interview Survey to examine mental health need and services utilization among populations of interest. The first brief compared prevalence of mental health need among veterans and non-veterans in CA and has been published in a peer-reviewed journal. The second study identified populations at greater risk for having unmet mental health needs and has also been recently accepted to a journal.

Harder+Company Community Research - Los Angeles, CA (2009-2013)
Research Associate
Served as key data and geographic information systems (GIS) analyst for the Los Angeles office. Managed teams of researchers working on a number of projects, including evaluations of the Los Angeles County Department of Mental Health's Innovation Program, Health Births Initiative, and supportive housing for transitional-age youth. Responsibilities include research design, data collection and analyses, report writing and dissemination, providing technical assistance, and building organizational capacity.

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Chapter 1: Introduction

Empirical research linking gentrification and health outcomes is scant, which may be due to methodological and data challenges (Huynh & Maroko, 2014; Morenoff et al., 2007). Given the rapid expansion of gentrification across California and nationwide, the public health implications of this phenomenon—its effects on morbidity, healthcare and societal costs, and health inequities—should be considered. This dissertation sought to examine the relationship between gentrification and adult mental health, to better understand the pathways by which gentrification potentially influences mental health, and to identify the populations most impacted.

Definition of Gentrification

The term “gentrification” was first introduced in the 1960s by Ruth Glass (1964), who described gentrification as a “process by which working class residential neighborhoods are rehabilitated by middle class homebuyers, landlords, and professional developers.” She distinguished gentrification from redevelopment, which she defined as the construction of new buildings as opposed to an upgrading of existing housing. Glass’s description of gentrification arose from observations of disinvestment in inner city neighborhoods, followed by urban renewal that attracted middle-class newcomers and displaced low-income residents. This process of disinvestment and reinvestment in low-income neighborhoods and the replacement of working-class residents by a middle-class “gentry” is known as “classic gentrification” (K. Shaw, 2008). Numerous stage models of classic gentrification have been presented, with no consensus among scholars (Kerstein, 1990). According to Clay (1979), neighborhoods undergoing early stages of gentrification experience an influx of new residents who renovate their properties. As more people move in and upgrade their homes, investors renovate houses for sale, and the neighborhood receives attention from media, city officials, and developers. Housing costs begin to rise, and lower income residents are forced to leave the neighborhood. Public and private investment intensifies, retail and professional services expand, home values and rent rapidly increase, and more low-income residents are displaced (Clay, 1979). Clay's model for classic gentrification suggests that gentrification is a linear process with an end stage. However, researchers have argued that gentrification is a "mutating process" with numerous forms and variations (Lees, Slater, & Wyly, 2008).

Glass's definition of gentrification has been expanded to represent a dynamic process and restructuring of the neighborhood (Lees et al., 2008; K. Shaw, 2008). Gentrification is a multidimensional and dynamic process that changes the physical, economic, social, and cultural characteristics of a neighborhood. Many researchers agree that neighborhoods undergoing gentrification experience an upscaling of the housing and/or commercial stock as well as a shift in the socioeconomic composition of residents (K. Shaw, 2008). Gentrification also changes the character of a neighborhood, is marked by higher levels of consumption, and is often linked to the displacement of original residents (Carpenter & Lees, 1995; Kennedy & Leonard, 2001). Gentrification can impact both urban and rural communities, and can take place in neighborhoods that are not in need of reinvestment (K. Shaw, 2008).

Physical Restructuring. A key feature of gentrification is the upgrading of the neighborhood's housing stock (Kennedy & Leonard, 2001). The physical landscape of a gentrifying neighborhood is altered through the rehabilitation of buildings, renovation or replacement of housing units, construction of new homes and apartment complexes, conversion of warehouses and vacant lots, and/or development of commercial districts (K. Shaw, 2008). As community-based organizations, developers, business associations, and government agencies invest more capital into the community, the neighborhood may undergo beautification. Streets and sidewalks are repaved, trees may be planted, and streetscape enhancements such as murals, public art, and parklets may be built to improve walkability and promote pedestrian activity.

Economic Growth. Upgrades in the housing stock increase the value of homes and properties. As public and private investments improve amenities and promote the gentrifying neighborhood as an attractive place to live, demand for housing increases. Under a constrained housing supply, rents and housing prices rise, and the neighborhood can lose affordable housing units (Atkinson, 2002; Zuk et al., 2015). As more middle- to high-income households who can afford the housing costs move in, and the economic profiles of gentrifying neighborhoods shift toward affluence. One potential benefit of this upward shift in household income is poverty de-concentration. However, evidence supporting this hypothesis is not conclusive (Atkinson, 2002; Lance Freeman, 2006). Local tax revenues do increase, which may be used to support city services and further improve neighborhood amenities such as parks and transportation services (Lance Freeman, 2006; Zuk et al., 2015). With more resources flowing in, gentrified neighborhoods may experience less crime. Studies investigating this hypothesis have, however, produced inconclusive results, which suggest that the impacts of gentrification on neighborhood crime are complex, potentially benefit some residents, and possibly harm others (M. S. Barton & Gruner, 2016; Kreager, Lyons, & Hays, 2011; Papachristos, Smith, Scherer, & Fugiero, 2011).

Social and Cultural Shifts. Gentrification is also marked by the in-migration of residents with higher socioeconomic status than original residents. Migrants who move to gentrifying neighborhoods are likely to be more educated, younger, non-Hispanic White, and less likely to have children (Ellen & O'Regan, 2011; L. Freeman, 2005; McKinnish, Walsh, & White, 2010). Residents who exit gentrifying neighborhoods tend to have lower incomes, are more often renters, and are more likely residents of color (Ding, Hwang, & Divringi, 2016; L. Freeman & Braconi, 2004; Zuk et al., 2015). Because of the strong link between race/ethnicity and income, the racial/ethnic composition of gentrified neighborhoods may shift to being more White or racially integrated. However, neighborhood racial transition is not always a consequence of gentrification (Ellen & O'Regan, 2011; McKinnish et al., 2010).

As more residents with middle- to high-incomes move to gentrifying neighborhoods, services and retail landscapes shift to meet the needs and preferences of new customers with more disposable income. The emergence of chain stores such as Starbucks and/or boutiques have been identified as a sign of commercial gentrification (S. Zukin et al., 2009). In their study on gentrification and crime, Papachristos and colleagues (2011) used the number of coffee shops located in a neighborhood to measure gentrification because coffee shops are “status product(s)” that meet “urban consumers’ demands…, demands which were mostly absent from the neighborhood’s prior population.” The new services and goods offered, however, may not be attainable by or meet the needs of long-term and/or low-income residents. Figure 1.1 illustrates neighborhood changes that arise from gentrification.

Conceptual Framework

The framework guiding this dissertation is the World Health Organization’s Framework for Action on the Social Determinants of Health (Solar & Irwin, 2010). Gentrification is a product of the socioeconomic and political context in which neighborhoods and cities are situated. Public investments, social policies, and cultural preferences for urban living, for example, influence supply and demand side processes that lead to gentrification. Once underway, the neighborhood changes associated with gentrification can impact residents’ living, material, and psychosocial circumstances, the intermediary determinants of health that determine their health and well-being (Solar & Irwin, 2010). The impacts of gentrification on residents’ intermediary determinants of health are heterogeneous and moderated by their socioeconomic positions. For example, a rise in housing value increases wealth for homeowners but can deplete the wealth and savings of renters paying higher rents.

A critical relationship in the conceptual framework is the relationship between socioeconomic position and neighborhood selection. Income, wealth, life course, personal preferences, and many other factors contribute to where people live and whether they live in low-income neighborhoods that then undergo gentrification. Socioeconomic characteristics also influence the behaviors and circumstances that affect health. In this framework, living in a gentrified neighborhood is a nonrandom process. Finally, gentrification can also affect residents’ living, material, and psychosocial circumstances and behaviors by altering social cohesion and social capital in their neighborhoods. Figure 1.2 depicts the pathways through which gentrification influences individuals' mental health. The following section details these pathways.

Physical Restructuring and Health. Through a physical restructuring of the neighborhood, residents potentially benefit from an upgrading in housing quality and conditions. Renovating and/or rehabilitating homes promotes "healthy homes" and can reduce residents' exposure to allergens, mold, and pests (Krieger & Higgins, 2002). In turn, their risks for mental health problems, infectious diseases, and chronic diseases are reduced. Streets and sidewalks may also be repaved and repainted, reducing the risk of injuries. Trees and other pedestrian-friendly enhancements promote healthy behaviors such as walking and biking. A key factor moderating the impact of physical restructuring on health is whether residents remain in the neighborhood to benefit from the new environment. Their abilities and decisions to stay in gentrifying neighborhoods depend on numerous factors, including income, social support, and homeownership status.

Economic Growth and Health. Economic growth attracts new businesses and can expand retail and food options for residents (Lance Freeman, 2006; Monroe Sullivan, 2014; S. Zukin et al., 2009). Economic growth can also increase police presence and security, reduce signs of neighborhood disorder, and increase perceptions of safety for some residents (M. S. Barton & Gruner, 2016). For those who are able to stay in the neighborhood and access these amenities, quality of life is enhanced, and emotional and physical well-being improves (Hill, Ross, & Angel, 2005).

Gentrification can also change the material circumstances of residents. Original residents potentially benefit from "incumbent upgrading," a phenomenon where residents who remain in the neighborhood experience increases in income (Ellen & O'Regan, 2011). In U.S. neighborhoods that experienced gains in income from 1990 to 2000, homeowners and renters who stayed in their neighborhoods experienced larger gains in average income compared to residents who stayed in neighborhoods that did not experience income gains. Researchers noted that incumbent upgrading potentially stems from selective retention of households who experienced gains in income and who chose to stay in the neighborhood (Ellen & O'Regan, 2011). Although not mentioned, gains in household income may also be a product of family members and households doubling up to ease their housing costs and stay in the neighborhood.

As demand for housing increases and home values rise, original homeowners experience gains in equity and wealth. In contrast, renters living in units not subject to rent control may see hikes in housing costs that outpace any gains in income. Housing burden, the proportion of income used to pay housing costs, increases, causing economic strain and stress for these residents. For some residents who choose and are able to remain in gentrifying neighborhoods, fear of displacement can contribute to secondary psychological distress (Atkinson, 2002; Lance Freeman, 2006; Newman & Wyly, 2006).

Social and Cultural Shifts and Health. Gentrification changes the character of a neighborhood. Residents who move to gentrifying neighborhoods have relatively higher socioeconomic status than original residents, many of whom are working-class. As the socioeconomic and, in some cases , racial/ethnic characteristics of the neighborhood change, original residents may experience cultural displacement, the replacement of their norms, culture, and values by the cohort of new residents (D. Hyra, 2015; Sharon Zukin, 2009). They may feel that new developments and activities such as bike lanes and festivals were not created not for them and may separate themselves from “outsiders” who recently moved to the neighborhood (Lance Freeman, 2006; Lees et al., 2008; S. Shaw & Sullivan, 2011). In addition, “boutiquing” of the neighborhood enhances quality of life for middle-class residents but may alienate long-term residents, engender community resentment, and erode social cohesion (Atkinson, 2002; Deener, 2007; D. S. Hyra, 2006; Sullivan & Shaw, 2011; Zhang & He, 2018; S. Zukin et al., 2009).

Residents' sense of belonging can also shift. Some original and new residents may embrace the changing character of the neighborhood; others may experience a sense of loss. For example, older residents in gentrifying neighborhoods, following the closure of important community institutions, felt socially disconnected and less secure in the neighborhood (Burns, Lavoie, & Rose, 2012). Social exclusion, reduced sense of belonging, and social division can negatively impact the mental and emotional health of residents in gentrifying neighborhoods.

At the neighborhood level, increased social mix in gentrifying neighborhoods has the potential to enhance the social networks and social capital of residents (Lance Freeman, 2006). However, interaction between long-term residents and newcomers may be limited (Chaskin & Joseph, 2011; Tach, 2009). Gentrification may also weaken community institutions, which typically foster civic and community participation, and has been linked to decreased voter turnout among long-term residents (Gibbs Knotts & Haspel, 2006; Putnam, 2001). In addition, high levels of residential mobility and displacement can disrupt social networks and collective efficacy, as well as sever important social ties that residents rely on for material and emotional support (Betancur, 2011; L. Freeman & Braconi, 2004; Newman & Wyly, 2006; Robert J. Sampson, Jeffrey D. Morenoff, & Gannon-Rowley, 2002). Finally, tensions between long-term and new residents can weaken social capital and social cohesion that influence collective efficacy and residents' health (Kawachi, Kennedy, & Glass, 1999; Kawachi, Kennedy, Lochner, & ProthrowStith, 1997).

Table 1.1 summarizes the pathways through which gentrification positively and negatively affects residents. Despite the documented advantages and disadvantages associated with gentrification, the public health field does not have a clear understanding of the mental health costs or benefits gentrification levies on residents. It's also unknown who is at greatest risk for serious psychological distress and should be prioritized in interventions when neighborhoods gentrify. This dissertation advances the small but growing literature on gentrification and its impact on health.

Overview of the Approach

Research Questions. This dissertation examined the following research questions:

1. **What are the mental health impacts of living in a neighborhood that is undergoing gentrification?**

   Hypothesis 1: Gentrification improves the living circumstances for some residents but may have negative psychological impacts. On average, gentrification increases psychological distress.

2. **Which subgroups are most affected by gentrification?**

   Hypothesis 2: On average, long-term residents, renters, and residents with low incomes are more susceptible to rising costs and more negatively affected by the changing character of gentrifying neighborhoods. These residents are more likely to experience serious psychological distress.

   Questions 1 and 2 were examined in Chapter 3.

3. **Does gentrification trigger within-neighborhood displacement, and does displacement affect adult mental health?**

   Hypothesis 3a: Residents of gentrified neighborhoods have greater risk of within-neighborhood displacement compared to adults living in not gentrified neighborhoods.

   Hypothesis 3b: Within-neighborhood displacement is significantly and positively associated with mental health distress.

   Question 3 was evaluated in Chapter 4.

Data Sources. The California Health Interview Survey (CHIS) is a population-based health survey that covers a wide range of health topics, including serious psychological distress, chronic health conditions, and access to care. CHIS is administered through a computer-assisted telephone interview (CATI) system and is conducted in English, Spanish, Cantonese, Mandarin, Korean, Tagalog (beginning

2014), and Vietnamese. CHIS also has rich sociodemographic information and oversamples hard-to-find subgroups. As a result of CHIS's sampling design and inclusion of underrepresented groups, study results reflect California's diverse population. To characterize neighborhoods and develop a measure of neighborhood change that identifies gentrified neighborhoods, we used data from the U.S. Census, American Community Survey, and Home Mortgage Disclosure Act reports.

Population of Focus. The study focused on adults aged 18 and over living in Los Angeles, Orange, Santa Barbara, San Bernardino, Riverside, or San Diego counties and who completed the CHIS interview on their own. Gentrification is a process that historically changes urban areas, city centers, or inner-city neighborhoods. Therefore, we also focused on adults living in urban census tracts with at least 500 residents.

Methods. We used multiple data sources to develop a measure that captures multiple dimensions of gentrification (Chapter 2). Using these measures of neighborhood change and five years of California Health Interview Survey data (2011, 2012, 2013, 2014, 2015), we compared non-equivalent groups of adults living in 1) low-income census tracts that underwent gentrification between 2010 and 2015, 2) low-income census tracts that did not undergo gentrification during the same period, 3) middle- to high-income tracts that experienced upscaling, and 4) middle- to high-income census tracts that did not experience upscaling. We performed a series of individual-level, cross-sectional regression analyses to test whether living in a gentrifying neighborhood increased residents' probabilities of having serious psychological distress in the past year (Chapter 3). Propensity score analyses, endogenous treatment effects modeling, and neighborhood matching were applied to address selective entry into gentrified neighborhoods and evaluate the degree to which current residents experienced change in gentrified or upscaled neighborhoods. We also employed instrumental variables estimation to address potential simultaneity between our key independent variable and outcome variable. Robust variance estimation was applied to adjust for clustering at the census tract level.

Gentrification can impact residents' mental health through increased housing burden and intensified pressures to move. In Chapter 4, we examined whether living in a gentrifying neighborhood increased residents' risks of within-neighborhood displacement, or moving to another residential unit in the same neighborhood because the previous unit was unaffordable, and then assessed whether experiencing within-neighborhood displacement affected residents' mental health.

Limitations

A key estimation challenge was selection bias. The relationship between gentrification and health may not be causal but a consequence of residential selection (Jokela, 2014, 2015). In this case, living in a gentrified neighborhood would be correlated with the error terms in outcome models, and estimated parameters for the gentrification variable would be biased. Propensity scores match or balance residents in low-income, gentrified neighborhoods to residents in low-income, not gentrified neighborhoods based on their probability for living in a gentrified census tract. This approach reduces bias and is robust against heterogeneity if models for estimating propensity scores were correctly specified and represented the probability of moving into a gentrified neighborhood. Correct specification requires variables that measure individuals' opportunities for and proximity to employment, personal preferences, and other motivations not covered in the California Health Interview Survey. Similarly, bivariate probit models are effective in reducing bias when exclusion restriction variables are strongly correlated with the probability of moving to a gentrified neighborhood but not (strongly) correlated with the outcomes of interest. We explored several instruments.

This dissertation focused on residents who lived in gentrified neighborhoods at the time they completed the CHIS survey (2011-2015). Study populations included residents who recently moved to the neighborhood as well as long-term residents who lived and remained in the neighborhood as it changed. One of the primary concerns surrounding gentrification, however, is direct residential displacement of incumbent residents. Given the California Health Interview Survey's cross-sectional sampling frame, we were unable to observe out-movers or residents who moved out of neighborhoods during the study period and could not determine where movers moved from and to. In turn, study results are subject to sample selection bias.

Strengths

This study is important for the following reasons. Whether deliberating future revenues, historical and cultural significance, or the displacement of current residents, community members and stakeholders must weigh the benefits and costs of developing or reinvesting in their communities. One factor that should be included in that calculation is the potential mental health cost of gentrification on pre-existing residents. This study attempted to measure the net effect of living in a gentrified neighborhood on risk for serious psychological distress, or a non-specific mental health diagnosis that can carry long-term consequences on individuals, their families, and communities. We sought to identify the populations most impacted by gentrification and compared the mental health impacts of gentrification on multiple resident groups including long-term and new residents, low-income residents, homeowners, and renters.

Using data from multiple sources, we applied three strategies for identifying gentrification that captures physical, economic, social, and cultural shifts in gentrifying neighborhoods. Many previous studies had concentrated on fewer dimensions and indicators to measure gentrification. We then compared the results, and tested the relationship between gentrification and mental health using all three measures in sensitivity analyses. In addition, we focused on a time frame (2011-2015) when the U.S. economy was in the process of recovering from the Great Recession (most recent studies on gentrification concentrated on periods between 2000 and 2010) and centered regions within which housing markets and prices rebounded more rapidly than many areas across the nation.

Given the limitations of the cross-sectional data, we employed numerous econometric techniques and approaches to reduce bias arising from residential selection and reverse causality, including instrumental variables estimation, and successfully identified promising instruments for neighborhood upscaling. Our primary data source was also an ideal dataset for understanding which groups were most affected by gentrification. Furthermore, questions related to moving in the California Health Interview Survey allowed us to identify another group of potentially impacted residents: within-neighborhood movers.

Evidence supporting a causal link between gentrification and mental health supports the public health field's increasing focus on social determinants of health and incorporating Health In All Policies (Rudolph, Caplan, Ben-Moshe, & Dillon, 2013). Results from this study potentially strengthen motivations for intersectoral collaborations between stakeholders in public health, city planning, housing policy and law, and development. From a healthcare delivery perspective, healthcare systems and providers can better serve their patients by understanding the potential health benefits or risk factors of living in a gentrifying neighborhood as well as challenges their patients might have when accessing care or adhering to care plans.

Figures and Tables

Figure 1.1. Products of Gentrification

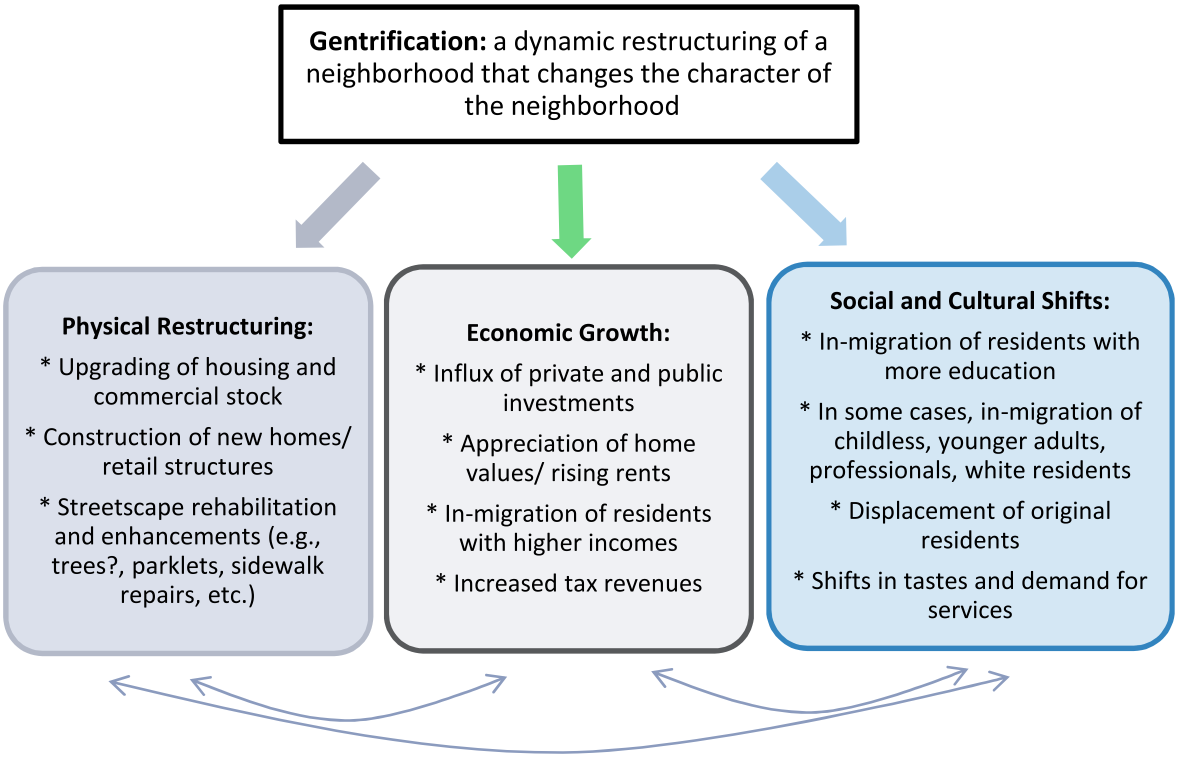


Figure 1.2. Conceptual Framework for Gentrification and Health

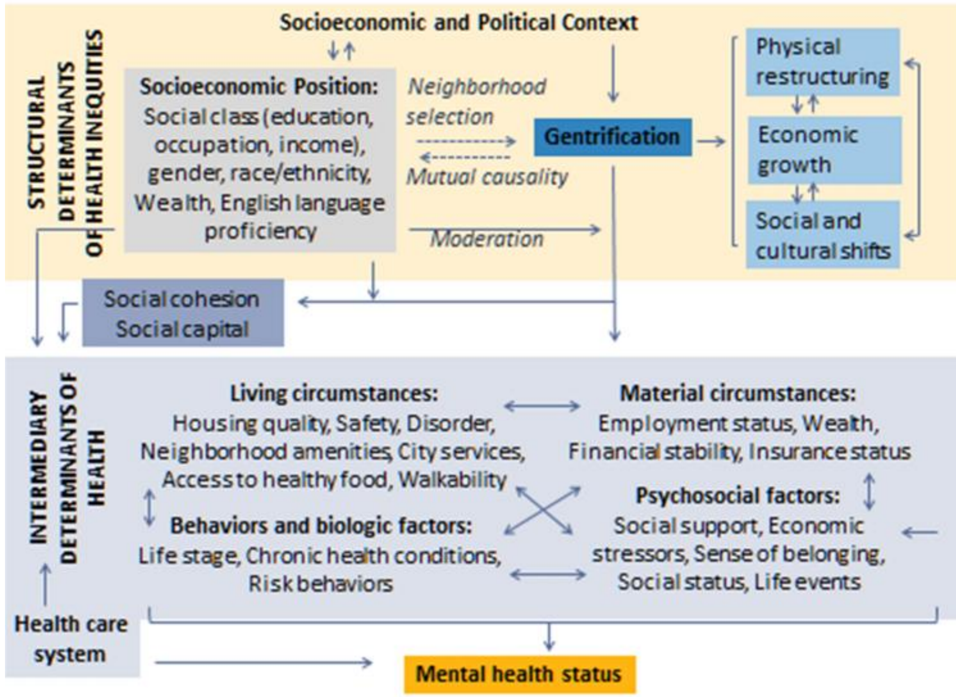


Table 1.1. Summary of Positive and Negative Impacts of Gentrification

	Positive	Negative
Neighborhood Impacts	• Increased safety • Increased social capital • Reduction in neighborhood disorder • Improved walkability	• Reduced social cohesion • Community tensions • Decreased social capital
Individual Impacts	• Wealth building • Improved access to healthy food • Improved housing quality • Improved neighborhood amenities and city services • Built environment that promotes active living	• Loss of social networks; decreased social support • Fear of displacement • Greater housing burden and financial instability • Reduced sense of belonging

Note: Benefits and costs associated with gentrification may not be experienced by all residents and are likely distributed across socioeconomic status and social location.

Chapter 2: Gentrified Southern California Neighborhoods

Introduction

Gentrification is a neighborhood transition process that impacts the material, living, and social circumstances of residents. While all neighborhoods evolve, gentrification is marked by the physical restructuring of neighborhoods, rapid economic growth, and notable shifts in the economic, social, and cultural characteristics of residents. The potential consequences of gentrification are multifaceted, complex, and can have both beneficial and deleterious effects on residents. In order to test or observe the impacts of gentrification on community members, we must be able to distinguish gentrifying neighborhoods from other neighborhoods.

Strategies for operationalizing gentrification are numerous and wide-ranging. Qualitative and quantitative strategies offer contrasting benefits and challenges. Qualitative studies provide richer descriptions of cultural and physical changes such as newly painted buildings or planted trees that are not readily quantifiable or available in large datasets. Qualitative studies often focus on single or small numbers of neighborhoods and incorporate discourse analysis of media and public reports, interviews with stakeholders, and direct observation (Boyd, 2008; Lance Freeman, 2006; Hammel & Wyly, 1996; S. Zukin et al., 2009). In contrast, quantitative strategies facilitate the examination of large geographic areas but have primarily relied on data collected by the U.S. Census Bureau, which, particularly for small geographic areas, are subject to measurement and sampling error and may not reflect all aspects of neighborhood change associated with gentrification (Bostic & Martin, 2003; Wyly & Hammel, 1999).

Various data sources and methods have been used in quantitative studies to identify gentrified neighborhoods, the most common of which is the threshold strategy where neighborhoods that meet certain conditions at the start of a study period and by the end of the study period are classified as gentrified (M. Barton, 2016). According to Lance Freeman, central city neighborhoods that previously experienced disinvestment and housed a large proportion of residents with low incomes were eligible for gentrification (L. Freeman, 2005). He operationalized this definition by identifying census tracts located in central cities that had lower proportions of housing built in the past 20 years than the median proportions of the metropolitan areas they were located in, and that had lower median incomes relative to their metropolitan areas. These tracts were then classified as gentrifying if they experienced increases in educational attainment and housing prices that were greater than increases in the metropolitan area (L. Freeman, 2005). Similar threshold strategies were employed in studies examining relationships between gentrification and transit-oriented development, residential mobility, and self-rated health (Chapple, Loukaitou-Sideris, Waddell, Chatman, & Ong, 2017; Ding et al., 2016; Gibbons & Barton, 2016).

Other quantitative methods for identifying gentrified neighborhoods involved ranking and principal components analysis (PCA). Using nine indicators Hammel and Wyly (1996) considered most effective for classifying gentrified tracts, Bostic and Martin (2003) ranked census tracts from 50 of the largest metropolitan statistical areas (MSAs) by indicator and classified “gentrifiable” tracts with the lowest average rank as “gentrifying.” Huynh and Maroko (2014) used a similar ranking strategy in their investigation of gentrification’s potential impact on pre-term birth by converting percent changes in three selected measures to z-scores, summing the z-scores, and then categorizing intensity of gentrification by quintile. A number of researchers used principal component analyses to operationalize and create gentrification scores. In their study of gentrification’s impact on voter turnout, Gibbs Knotts and Haspel (2006) used a principal components model to reduce Census indicators to a single measure. Owens (2012) also used PCA to create a measure of neighborhood socioeconomic status (SES). She defined ascent as neighborhoods whose SES percentile score relative to other neighborhoods in their MSAs increased at least by 10 percentile points from one period to the next. And in a recent study that examined the impact of displacement on healthcare utilization, authors also applied PCA to reduce initial and growth rankings in median household income, median rent, and proportion of college graduates (6 rankings total) into two components (Lim et al., 2017). PCA loading scores were then used to define neighborhoods as gentrifying or non-gentrifying.

As mentioned earlier, Census data have been the primary data source for identifying gentrified neighborhoods for several reasons. First, the scope of data collection by the U.S. Census Bureau is national, which allows researchers to expand their study areas. Many Census surveys are collected continuously or annually, allowing for trend analyses, and Census data are often available for small geographic areas such as census tracts and block groups. While rich in housing, economic, and sociodemographic information, surveys such as the American Community Survey and American Housing Survey are less effective in measuring cultural shifts or changes to the physical landscapes of neighborhoods. Estimates at the census tract or block group levels are also subject to larger standard errors, which make detection of meaningful changes more challenging.

In recognition of the limitations of relying on Census data, researchers incorporated data from additional sources. Indicators from these sources measured dimensions of neighborhood change such as physical restructuring and cultural shift that are not available in Census data. To capture cultural changes within neighborhoods, Papachristos and colleagues (2011) compared the numbers of coffee shops in a neighborhood at different time periods. Researchers have also analyzed parcel data compiled by County Assessor's Offices to observe new construction of residential structures, land-use changes, major renovations, and property conversions (Chapple et al., 2017), used dollar amount of mortgage loans as a proxy for neighborhood reinvestment (Lance Freeman, 2006; Kreager et al., 2011), and included the numbers and types of establishments moving to and away from neighborhoods as indicators for accelerated commercial activity and industrial displacement (Curran, 2007; Lance Freeman, 2006).

The methods and measures used to identify gentrified neighborhoods are important because they direct attention and potentially resources and policy action toward select neighborhoods that may or may not have underwent gentrification. Moreover, different strategies for developing a gentrification variable, when used as an independent variable, may produce conflicting results. Michael Barton (2016) demonstrated this point by replicating two census-based quantitative strategies to identify gentrified neighborhoods in New York City and compared the results against neighborhoods reported as gentrified by the New York Times. Results showed that the number and geographic distribution of gentrified neighborhoods varied greatly by strategy (M. Barton, 2016). This study aimed to advance research on quantitative approaches to identifying gentrification by applying three strategies that captured multiple dimensions of neighborhood upscaling. We sought to identify neighborhoods that underwent gentrification between 2010 and 2015 across six Southern California counties: Ventura, Los Angeles, Orange, Riverside, San Bernardino, and San Diego. We applied two empirically-driven strategies, principal components analysis and cluster analysis, replicated a threshold strategy, and compared the results.

Methods

Unit of analysis. The geographic boundary of a neighborhood, and therefore unit of analysis, was the census tract. Census tracts are statistical subdivisions of counties or equivalent entities (U.S. Census Bureau, 2012). Census tracts are small, relatively stable geographic units with populations between 1,200 and 8,000 people. Although geographically smaller than some communities, census tracts were selected because gentrification often occurs in parts of a neighborhood as opposed to the entire neighborhood and census tracts provide higher spatial resolution to a dynamic process that may be masked when using larger units (Chapple et al., 2017; Lance Freeman, 2006).

Data Sources. We used data from two public datasets: American Community Survey and Home Mortgage Disclosure Act (HMDA) Disclosure Reports. The American Community Survey (ACS) is an ongoing national survey conducted by the U.S. Census Bureau. Approximately 2.5% of U.S. households are surveyed annually. Survey topics include housing characteristics as well as household and respondent demographics, socioeconomic status, and health. The Census publishes detailed tables summarizing housing and population characteristics of geographic areas as small as census blocks using five years of pooled data. Five-year 2006-2010 and 2010-2015 estimates[1] measuring the economic, social, and cultural characteristics of a neighborhood were extracted for census tracts in Los Angeles, Orange, Ventura, San Bernardino, Riverside, and San Diego counties and merged by state, county, and census tract Federal Information Processing Standard Publication (FIPS) codes. The U.S. Census Bureau also releases 1-year and 3-year estimates, but given that neighborhood changes were expected to be small, we selected the 5-year estimates, which are more reliable and precise (U.S. Department of Commerce, 2018).

The Home Mortgage Disclosure Act (HMDA) requires lending institutions to disclose their home mortgage and home improvement lending activity. The Federal Financial Institutions Examination Council (FFIEC) aggregates these disclosure statements and publishes reports by Metropolitan Statistical Area/Metropolitan Division. Summaries of home loan originations, home improvement loans, and refinancings in Aggregate Table 1 were extracted by census tract for 2010 and 2015 to measure changes in home investments and loans.

There were 4,553 census tracts across all six counties in the 2006-2010 American Community Survey dataset, all of which, with the exception of Tract 9304.01 in Los Angeles County (99.9%), were merged with 2011-2015 American Community Survey data. With the exception of Tract 1370 in Los Angeles County, all 4,553 (99.9%) tracts in the 2011-2015 dataset were successfully merged with 2006-2010 data. A total of 4,552 census tracts had both 2006-2010 and 2011-2015 data. Home loan originations in 2010 were originally aggregated to 2000 census tract boundaries. To assess changes

[1] Five-year estimates include data collected during the time period. For example, 2006-2010 estimates include data collected between January 1, 2006 and December 31, 2010.

within approximately the same census tract, numbers and total dollar amounts of loans originated were reallocated to Census 2010 boundaries by applying interpolating weights and methods used by Logan, Xu, and Stults (2014). There were 4,542 tracts in the reallocated 2010 dataset, 4,508 (99.3%) of which were merged with 2015 data; 4,508 of 4,511 (99.9%) tracts in the 2015 dataset were merged with 2010 data.

The ACS and HMDA datasets were then merged by FIPS codes, and 4,540 of 4,554 (99.7%) tracts in the ACS dataset were merged with HMDA data; 4,540 of 4,548 (99.8%) of census tracts in the HMDA dataset were merged with ACS data. The ACS and HMDA merged dataset had 4,562 unique records or census tracts; 4,507 tracts (98.8%) had data from both datasets and years. 4,448 fully or partially urban census tracts with 500 or more residents were retained for analysis.

Measures. We defined gentrified neighborhoods as neighborhoods with high proportions of low-income households that experienced rapid physical restructuring and economic growth during the study period. Unlike neighborhoods undergoing renewal or resurgence with current residents in place, gentrified neighborhoods are also characterized by the in-migration of residents with higher socioeconomic status than current residents as well as the displacement of lower income residents. These migration patterns change the character of the neighborhood. Therefore, identification of candidate indicators of upscaling were guided by three dimensions of neighborhood change: 1) physical restructuring, 2) economic growth, and 3) cultural and social change due to in-migration of residents with high socioeconomic status. Table 2.1 lists measures considered for each dimension and used in analyses. Indicators in grey were not selected due to non-availability or mismeasurement concerns. All dollar amounts were adjusted to 2015 dollars using the Consumer Price Index Inflation Calculator.

Physical restructuring includes the construction of new residential or commercial units, modifications or improvements to existing structures, changes to streets and sidewalks, new signage, and other physical features in neighborhoods (K. Shaw, 2008). Without direct observations or photo analyses of neighborhoods before and after the study period, detecting subtle changes such as repaved roads or renovations is difficult. We considered measures that indicated new construction, changes in the types of homes constructed, changes in property use, and investments in home improvement.

Gentrifying neighborhoods often receive investments from local agencies and community-based organizations. Financial institutions may also be more inclined to lend to businesses in these neighborhoods. In turn, economic activity increases in gentrifying neighborhoods. As gentrifying neighborhoods become more attractive to households and entrepreneurs, residential and commercial values rise and the economic profiles of residents change to reflect in-movers with higher household incomes. Census indicators have been widely applied to measure changes in home values, rent, and household income and were also used in this study (Bostic & Martin, 2003; L. Freeman, 2005; Gibbons & Barton, 2016; Hammel & Wyly, 1996). Increased investment was measured by changes in average loan amounts secured for home purchases and home improvement loan amount per capita (Lance Freeman, 2006; Kreager et al., 2011). At the time of the study, we were unable to secure and include measures that reflect changes in economic activity.

<u>Multiple Imputation of Top-Coded Median Home Values and Rents.</u> Median home values were top-coded at $1M for 196 census tracts in 2006-2010; 22 tracts were top-coded at $2M in 2011-2015. To reduce errors and minimize reductions in sample size from missing values, we imputed top-coded 2006-2010 median home and median rent values using interval regression for a partially observed continuous variable. Independent variables used to impute censored values included 2006-2010 estimates for improvement loan amount per capita, median household income, number of housing units, average home loan amount, percent of household with incomes above 200% FPL, total number of households, rental vacancy rate, owner vacancy rate, homeownership rate, racial/ethnic composition of residents, percent residents with Bachelor's degrees or more, percent of owner-occupied homes with values over $500,000, percent of rental units with rents over $1,500, employment rate, and percent of employed

people in management, business, science, and arts occupations. Median rents and home values in 2011-2015 were also used to respectively impute censored 2006-2010 median rents and home values. We estimated 20 imputations for each censored value and randomly selected 5 to be used in analyses.

Gentrification is principally a class-based phenomenon, so although residents moving to gentrified neighborhoods may have higher incomes than current residents, education is a more appropriate marker for class (L. Freeman, 2005; Gibbs Knotts & Haspel, 2006; Hammel & Wyly, 1996). Classifying residents by education also includes the in-migration of professionals and artists, who are often considered as pioneers of gentrification, into lower income neighborhoods (Clay, 1979; Kennedy & Leonard, 2001). We considered changes in the proportions of residents with at least a Bachelor's degree as well as proportions of residents working in management, business, science, or the arts as indicators of class transition. It would also be a mistake to ignore the role race/ethnicity has on influencing which neighborhoods gentrify as well as gentrification's effects on longtime residents and residents of color (Drew, 2012; J. Hwang, 2016; Jackelyn Hwang & Sampson, 2014; Mumm, 2015; S. Shaw & Sullivan, 2011). Changes in the proportion of non-Hispanic White residents from 2010 to 2015 as well as changes in age composition and family types were also considered as markers of social and cultural change.

As shown in Table 2.1, not all proposed measures were included in our analyses. Selected measures had to meet set criteria. Measures must be 1) consistent across geographic boundaries, 2) available in 2010 and 2015, and 3) consistent in data collection and variable construction. Issues related to mismeasurement, high standard errors, and missing and imputed values were also considered when selecting indicators of neighborhood change.

Analyses. Three strategies were applied to identify upscaled neighborhoods, or neighborhoods that experienced rapid physical restructuring, economic growth, and cultural and social shift from 2010 to 2015. All analyses were stratified by county to situate neighborhoods within their respective regional contexts.

Strategy 1: Under this approach, indicators of physical restructuring, economic growth, and social and cultural change influence the latent construct of neighborhood upscaling or, for historically under-resourced communities, gentrification. We conducted principal components analysis (PCA) to represent the variances of eight neighborhood change indicators: 1) change in dollar amount of improvement loans per capita, 2) change in median household income, 3) change in median home value, 4) change in mean dollar amount for home loans, 5) change in median rent, 6) change in percent of households with incomes above 200% FPL, 7) change in percent of adults aged 25+ with a college degree, and 8) change in percent of non-Hispanic White residents. Eigenvalues and parallel analyses were used to determine the maximum number of components to retain (Glorfeld, 1995; Horn, 1965). PCA was performed with promax rotation to allow correlation between principal component loadings.

Principal component scores were then binned into groups using a clustering approach that, given k groups, minimizes the sum of squared deviations from group means (Fisher, 1958). This approach maximizes homogeneity within groups. "Upscaled" census tracts were classified as tracts in the group with the greatest PCA scores. This strategy was repeated with five imputed median home values and median rents. Results were reviewed for consistency across imputed sets.

Strategy 2: Using the same eight neighborhood change indicators, we conducted K-medians cluster analysis to determine the natural groupings of census tracts in each county. K-medians cluster analysis partitions observations into distinct, non-overlapping groups (StataCorp, 2017). Researchers determine the number of k groups, and observations are iteratively assigned to the group whose median is closest. The group medians are then recalculated, and the process is repeated until all observations are assigned to a group. We initially clustered census tracts into 2 to 6 groups, and then used the Caliński-Harabasz pseudo-F index and Duda-Hart Je(2)/Je(1) stopping rules to determine the k groups that have the most distinct clustering. We selected the groupings that had the most noticeably distinct clusters. Cluster analyses were repeated with five imputed median home values and median rents, and results were reviewed for consistency across imputed values. Tracts in the group with the largest group median were classified as “upscaled.”

To reduce the influence of outliers we repeated the PCA and cluster analyses with standardized change indicators.

Strategy 3: This approach replicated the threshold strategy used by Urban Displacement Project researchers (Chapple et al., 2017). Census tracts were considered “upscaled” if they experienced demographic change and rent increases that outpaced county rates. Specifically, “upscaled” census tracts experienced 1) a greater percentage point increase in the proportion of college educated adults compared to the county, 2) greater percentage point increase in the proportion of non-Hispanic White residents, 3) greater increase in household income, and 4) greater increase in median gross rent compared to the county (Chapple et al., 2017). It should be acknowledged that this approach did not take into account increases in home values or home improvement loans, and prioritized rental inflation as a condition for gentrification, which may be more responsible for displacement than rising home values (L. Freeman, 2005).

All three strategies offered advantages and disadvantages to identifying upscaled census tracts. Principal components analysis is a data reduction technique. Principal components maximize the variance of indicators, and component scores represent the weighted linear combination of indicators. PCA allows correlation between components, which is useful if we assume that economic growth in a neighborhood is correlated with social and cultural change, for example. Once principal components are generated, interpretation of what they represent is subjective, and researchers must decide how to use component or overall scores to classify neighborhood upscaling.

Similar to PCA, K-medians cluster analysis can synthesize or summarize large numbers of neighborhood change indicators. K-medians cluster analysis is an exploratory data analysis technique that partitions observations into groups; its procedures and algorithms are uncomplicated. Groups are determined by the similarity and dissimilarity of observations, but correlations between indicators are not considered.

Unlike PCA and K-medians cluster analysis, indicators have equal weight under the threshold strategy. The proportion of tracts that meet threshold strategy requirements falls steeply as the number of thresholds or indicators increases. The primary advantage of the threshold strategy, however, is its comprehensibility. Under this strategy, upscaled or gentrified neighborhoods are census tracts that outpaced their respective counties in household income growth, median rent increases, increases in highly educated residents, and increases in non-Hispanic White residents. Table 2.2 summarizes the advantages and disadvantages associated with each strategy.

By definition, gentrification is a process that impacts low-income neighborhoods. Therefore, we distinguished historically low-income neighborhoods from middle- to high-income neighborhoods, and defined neighborhoods with median incomes below 80% of their respective counties' median household incomes at the start of the study period (2006-2010) as "Low-income." "Middle- to high-income" neighborhoods had median household incomes at or above 80% of the county median income. Using each strategy, all census tracts with non-missing indicators were categorized as: "Low-income and gentrified," "Low-income and not gentrified," "Middle- to high-income and upscaled," or "Middle- to high-income and not upscaled."

Overlap across Strategies. Degrees of association between results generated from all three strategies were assessed through bivariate analyses and by calculating phi coefficients. All analyses were conducted using Stata 15.

Results

Approximately one-third (n=1,375) of census tracts in Southern California had median household incomes below 80 percent of their counties' median incomes in 2006-2010 and therefore were vulnerable to gentrification. K-medians cluster analysis identified the fewest number of gentrified tracts (n=145), followed by the threshold strategy (n=203). See Table 2.3. As many as 332 census tracts gentrified between 2010 and 2015 based on principal components analysis results. Across all three strategies, fewer than 8 percent of Southern California neighborhoods gentrified during the study period.

Table 2.4 presents cross-tabulations of gentrified versus not gentrified low-income tracts by strategy. Nearly half of gentrified tracts identified using cluster analyses (46%) and the threshold strategy (45%) were also classified as gentrified using PCA. Gentrified tracts identified using cluster analysis and the threshold strategy were the most distinct; 23 percent of gentrified tracts using cluster analysis were also gentrified using the threshold strategy, and only 16 percent of gentrified tracts using the threshold strategy were gentrified using cluster analysis.

Among middle- to high-income tracts, 59 percent of upscaled tracts identified by the threshold strategy were also classified as upscaled using PCA (Table 2.5). Only 29 percent of upscaled tracts using the threshold strategy were considered upscaled using cluster analysis.

Table 2.6 summarizes the numbers and proportions of census tracts identified as upscaled across a combination of strategies. Nearly 60 percent of tracts were considered not upscaled across all three strategies. The second largest category represented 644 tracts (15%) that were classified as upscaled only through principal components analysis. An additional 435 tracts (10%) were classified as upscaled only through cluster analysis. The threshold strategy identified 178 upscaled tracts (4%) that were classified as not upscaled using the other two strategies.

As many as 328 census tracts (8%) were identified as upscaled by both PCA and cluster analysis strategies. PCA and the threshold strategy both identified a total of 225 tracts (5%) as upscaled, and 98 tracts (2%) were classified as upscaled using both the threshold strategy and cluster analysis. Only 74 tracts were classified as upscaled by all three strategies.

Phi coefficients comparing gentrified versus not gentrified tracts across strategies reflect the above results and indicate that associations between results were weak (Table 2.7). The phi coefficient between the principal components analysis results and results using cluster analysis and the threshold strategy were .27 and .31, respectively. With a phi coefficient of .16, cluster analysis and threshold strategy results were most dissimilar.

Sensitivity Analyses. To examine the influence of outliers, we replicated the principal component analyses and cluster analyses using standardized neighborhood change indicators (8 total). Results using PCA did not change; upscaled tracts identified using raw and standardized neighborhood change indicators did not change across counties. Cluster analysis results using standardized data, however, differed considerably from results using original data. First, the number of distinct clusters drops from 3 groups to 2 groups for most counties. Fewer clusters contributed to larger numbers of census tracts that were classified as upscaled. With the exception of Riverside County, at least 46 percent of tracts in each county were tagged as upscaled using standardized indicators; 1,974 tracts were tagged as upscaled using standardized indicators compared to 787 tracts when using indicators in the original scales.

Discussion

Our study compared three strategies for identifying upscaled or gentrified neighborhoods. Overall, the number of gentrified neighborhoods varied substantially by strategy, and overlap across results was minimal to low. The threshold strategy, which was informed by a predetermined concept of upscaling, was the most restrictive strategy in that it identified the least number of upscaled census tracts. Only 1 in 10 census tracts in Southern California were classified as upscaled, compared to 18 percent of census tracts using cluster analysis and 26 percent using principal components analysis. At a maximum, classifying one-fourth of all neighborhoods as upscaled appeared reasonable; a higher fraction would likely include neighborhoods that experienced secular changes but not rapid change and growth at the pace of upscaled tracts. Based on our study results, no more than 8 percent of neighborhoods in Southern California gentrified from 2010 to 2015, which falls within the range identified in other studies (Chapple et al., 2017; Ding et al., 2016; L. Freeman, 2005). See Results by County in the Supplemental Materials section for details.

The threshold strategy in our study defined upscaling as growth in the rental market and substantial changes in the profile of residents who are more affluent, educated, and non-Hispanic White. Census tracts classified as upscaled using this strategy on average experienced the greatest growth (or smallest declines) across all criteria. Although the threshold strategy definition for upscaling is mostly consistent with how gentrification has been characterized in earlier studies, the criterion that the non-Hispanic White population increases does not reflect gentrification observed in many neighborhoods across the U.S. (Escalante, 2017; D. S. Hyra, 2006; Moore, 2009). Gentrification has not always resulted in racial transition of neighborhoods (Ellen & O'Regan, 2011), and gentrifiers can share the same race or ethnicity of existing residents, such as in Boyle Heights, a Latino enclave near downtown Los Angeles, where longtime residents are resisting the “gentefication” of their neighborhood by college-educated and upwardly mobile Latinx[2] people (Delgadillo, 2016). In cases where cultural shifts in upscaling neighborhoods are solely class-based and does not contribute to racial transition, the current specification of the threshold strategy would misclassify upscaled or gentrified neighborhoods as not upscaled. Misclassification may be more likely in regions like Southern California where the non-Hispanic White population has declined. Future applications of the threshold strategy should reconsider the criterion that the proportion of non-Hispanic White residents increase, or downgrade its importance relative to other criteria.

[2] 'Latinx' is a gender-neutral word for people of Latin American descent or identity and is used in lieu of Latino or Latina.

Unlike the other two strategies, the threshold strategy focused on four of the eight neighborhood change indicators in our study and required that change in all four indicators exceeded change at the county level. Changes in home investment and home values and shifts in the proportion of middle- to high-income residents were not factored into the identification of upscaled neighborhoods. The exclusion of these indicators may partially explain low overlap between upscaled neighborhoods using the threshold strategy and upscaled neighborhoods using PCA or cluster analysis. And as mentioned above, the criterion that non-Hispanic White residents increase more rapidly than countywide also likely contributed to the 178 census tracts that were classified as upscaled only under the threshold strategy. This indicator carried less weight when conducting principal component analysis and cluster analysis.

The threshold strategy applied an a priori concept of gentrification to identify upscaling. Upscaling as determined by using principal components analysis and cluster analysis was constructed from the variance of neighborhood change indicators within each county. The PCA strategy identified the largest number of upscaled tracts; roughly a quarter were considered upscaled. Under this strategy, the first principal component accounts for the largest amount of variance across neighborhood change indicators. Housing investments and rising home prices represented the first principal component for census tracts in Los Angeles County, which suggests that housing market activities were especially volatile in this county. Shifts in household income and the affluence of residents accounted for the most variance among census tracts in all other Southern California counties. In contrast to the threshold strategy, PCA allowed neighborhood change indicators to have different influences on a metric for upscaling, which varied from county to county. This flexibility is advantageous because it does not confine the neighborhood change processes of urban cores (e.g., Los Angeles County), suburbs (e.g., Orange County), and exurbs (e.g., Riverside and San Bernardino) to the same definition. Also unlike the threshold strategy, upscaled tracts using PCA did not have the greatest mean increases across most indicators, which complicated the narrative of upscaling for each county.

Cluster analysis is also an empirically-driven strategy that binned census tracts into groups based on their similarity. This exploratory analysis tool also allowed some indicators to carry more weight in the binning process than others. As a result, upscaled tracts using cluster analysis had the greatest mean increase in some indicators and not others compared to upscaled tracts using other strategies. Interpretation of the groups was considerably more complicated and subjective compared to translating principal components. For example, a 3-cluster solution could identify a group of census tracts in which investment, home values, median rents, and the socioeconomic profile of residents have declined. These tracts would have been classified as not upscaled. For the two remaining clusters, one group could have very high mean increases in loan amounts, increases in home value, and gains in household income, while the other group of census tracts had greater average increases in rents and proportions of highly educated residents. The analyst must then decide whether to classify one or both groups as upscaled. Without a clear definition of upscaling (as demonstrated by the threshold strategy), cataloging clusters is likely variable across researchers. Sensitivity analyses also showed that, unlike PCA, K-median cluster analysis was sensitive to data transformations (i.e., standardized indicators) and generated very different groups than when using original scales. Only 3 percent of census tracts in Southern California were considered gentrified (low-income and upscaled) using cluster analysis, which makes this strategy the most restrictive for identifying gentrified tracts. Upscaled tracts identified by cluster analysis were least similar to results using the threshold strategy.

Notably, nearly half of upscaled tracts using the threshold strategy were low-income and therefore vulnerable to gentrification, compared to only 30% of low-income tracts using PCA and 18% of tracts using cluster analysis. One interpretation of this finding is that despite focusing on four indicators, the threshold strategy prioritizes neighborhood changes that are more common in upscaled and low-income, in other words, gentrified communities. In contrast, cluster analysis and to a lesser extent PCA may be more sensitive to detecting upscaling among middle- to high-income neighborhoods. This explanation is further supported by the fact that housing market indicators such as changes in home improvement and purchase loans and median home values were absent in the threshold strategy, and middle- to high-income neighborhoods had much higher numbers of owner-occupied units compared to low-income communities. Therefore, surges in rent may be more relevant in upscaling low-income communities with higher proportions of renters, and increases in home prices and or loans may be more characteristic of upscaling middle- to high-income neighborhoods with greater proportions of home owners.

If some neighborhood change indicators are more relevant to low-income neighborhoods and less to middle- to high-income neighborhoods, we speculate whether the identification of upscaled neighborhoods should be conducted by neighborhood type (i.e., affluence, housing tenure, etc.) as opposed to classifying upscaling among all neighborhoods within a county. The implication that low-income neighborhoods experience upscaling differently from middle-income neighborhoods needs further examination.

Limitations

Our study has several limitations. We would have preferred to use more indicators for each dimension of upscaling (i.e., physical restructuring, economic growth, and cultural shift). With one available indicator for the physical restructuring dimension, change in dollar amount of home improvement loans per capita, our study focused on individual investments in their homes. We were unable to observe changes in public and private investments in new housing, commercial development, and neighborhood improvements. Such information may be available for smaller geographies, but are less reliable across 4,300+ tracts in Southern California. Our study did prioritize data quality and selected neighborhood change indicators that met a set of requirements to reduce mismeasurement.

The strategies applied in this study also did not explicitly distinguish upscaling arising from migration (moves in and out of neighborhoods) or incumbent upgrading, upscaling with current residents remaining in place. Upscaling driven by existing and longtime residents is considered by many stakeholders as desirable. Upscaling that is driven by selective in-migration and, in many cases, displacement potentially decreases quality of life for pre-existing residents. This latter form of upscaling, otherwise known as gentrification, was the focus of our study. By including indicators such as change in the proportion of residents with Bachelor's degrees and change in the proportion of non-Hispanic White residents, census tracts with substantial changes were more likely to be classified as upscaled. In this respect, the threshold strategy is more likely to identify upscaled tracts with higher mobility rates. If in-migration and/or displacement are considered conditions for gentrification, more direct measures such as the fraction of new residents should be considered in future efforts to identify gentrified neighborhoods.

Gentrification is a long-term process that spans across business and housing cycles. Our study examined neighborhood change during a period of expansion following the 2008 housing and financial crises. Therefore, our results are confounded with short-term changes driven by the recovery period, which potentially influenced the numbers and profiles of neighborhoods considered upscaled. Future studies can consider examining the long-term trajectories of neighborhoods identified as gentrified. In addition, the study period, 2010-2015, is relatively short compared to most prior studies of gentrification. Although a longer period may reflect the process of gentrification in some regions and time periods, the process of gentrification may be accelerated in places like the San Francisco Bay Area or Southern California where vacancy rates are low and housing prices and rents have climbed more quickly than in other areas. Our results showed that substantial neighborhood change can occur in upscaled neighborhoods relative to non-upscaled neighborhoods in a short period.

Our study demonstrates that conceptually- and empirically-driven strategies for identifying gentrified neighborhoods generate greatly different results. Findings mirror conclusions by Barton (2016) and are not surprising given that consensus on the definition of gentrification and the most effective strategy for recognizing it has not been reached. Our study results highlighted the importance of the identification strategy when examining gentrification and began to clarify differences across strategies. Future efforts to identify gentrified neighborhoods should continue to include the economic characteristics of residents as well as rent surges, which applied more heavily to upscaled low-income neighborhoods as opposed to upscaled middle- to high-income neighborhoods. We would also explore other data sources such as Longitudinal Employer-Household Dynamics and parcel data to include additional indicators of physical restructuring in neighborhoods. By observing changes in retail density, property use codes, and new construction, we can gain a better understanding of how closely physical restructuring follows gentrification.

Figures and Tables

Table 2.1. Candidate Measures of Physical Restructuring, Economic Growth, and Social and Cultural Change

Physical Restructuring						
Construct	**Measure (variable type)**	**Source(s)**	**Construction of Measure**	**Direction of Association**	**Notes and Justification**	**Limitations**
Upgraded housing	Change in dollar amount of home improvement loans originated per capita (continuous)	Home Mortgage Disclosure Act (HMDA) LAR	Recoded: (Total dollar amount of originated loans in 2015/total number of residents in 2015)-(total dollar amount of originated loans in 2010 /total number of residents in 2010); 2010 values adjusted to 2015 dollars using CPI.	Positive	Increases in loans secured for home improvement indicate a rise in home investment and an upgrading of housing units.	Total amount of home improvement loans approved do not perfectly translate to dollars spent on home improvement and increased value. Note: Factor change considered but large number of tracts would be lost due to $0 improvement loans in 2010.
Construction of new housing units	Change in proportion new housing units (continuous)	American Community Survey (DP04)	Recoded: (Housing units built in 2010 or later/total number of housing units)-(housing units built in 2005 or later/total housing units)	Positive	Increases in the proportion of new homes built in the past 5 years signal an increase in the pace of home construction in the neighborhood.	ACS data samples approximately 2.5% of the U.S. population per year. More than 50% of tracts had “0” new structures built in the past five years. Margin of errors are large. Measure would likely introduce more noise than information.

Physical Restructuring						
Construct	**Measure (variable type)**	**Source(s)**	**Construction of Measure**	**Direction of Association**	**Notes and Justification**	**Limitations**
Types of homes constructed	Absolute change in median number of rooms (continuous)	American Community Survey (DP04)	Recoded: Absolute(Median rooms in 2015-median rooms in 2010)	Positive	Changes in the median number of rooms also indicate shifts in the type and size of new housing units.	It's unclear whether gentrification contributes to the construction of larger or smaller housing units and whether changes in the median value will be observed within 5 years. ACS data are subject to high standard errors.
Land use designations	Change in property use code	Parcel Data from County Assessor's Offices, compiled by Core Logic		Positive	Zoning designation changes indicate public actions for development.	Data not consistent across all counties, require substantial cleaning, and may be incomplete.
Retail density	Change in number establishments per square mile	Census Bureau County Business Patterns, business directories		Positive	Increase in retail density suggests the neighborhood may be experiencing commercial gentrification.	Not available at the census tract level. LEHD Origin-Destination Employment Statistics, Workplace Area Characteristics may be used in future research to assess change in number of jobs per neighborhood.

Physical Restructuring						
Construct	Measure (variable type)	Source(s)	Construction of Measure	Direction of Association	Notes and Justification	Limitations
Home and retail construction	Permits	Building Permits Survey		Positive	Permits are required for new construction.	Not readily available by census tract, but may be geocoded if collected from counties and permit-issuing places.
Construction of housing new units	Change in number of newly constructed units	Parcel Data from County Assessor's Offices, compiled by Core Logic		Positive	Parcel data include information on years structures were built.	Initial assessments of the data and comparisons with one-year ACS estimates suggest that the estimated number of new units were underreported and that data require substantial cleaning.

Note: Measures in grey were not included in study.

Economic Growth						
Construct	**Measure (variable type)**	**Source(s)**	**Construction of Measure**	**Direction of Association**	**Notes and Justification**	**Limitations**
Individual economic status	Change in median household income (continuous)	American Community Survey (S1903)	Median household income in 2015/median household income in 2010 (adjusted 2015 dollars using CPI)	Positive	Increases in median income signal in-migration of residents with higher SES and a rise in buying power in the neighborhood.	Measure could also capture incumbent upgrading, increases in income among original residents. ACS data are subject to high standard errors.

Economic Growth						
Construct	**Measure (variable type)**	**Source(s)**	**Construction of Measure**	**Direction of Association**	**Notes and Justification**	**Limitations**
Real estate market - value	Change in median home value (continuous)	American Community Survey (DP04)	Median home value in 2015 – median home value in 2010 (adjusted 2015 dollars using CPI); Note: Home values were top-coded at $1M for 196 (4.5%) tracts in 2010. Median home values for these tracts were imputed (m=20) using interval regression for a continuous partially observed (censored) variable method.	Positive	Rise in home values signal an upgrading of the neighborhood, increased demand, and economic growth, including tax revenues.	Median home values were self-reported and do not precisely reflect the market home values. Reported home values were top-coded at different values in different years. 2010 values were imputed for top-coded tracts to approximate true changes in median home values, and prevent exclusion of 196 tracts from analyses. Tracts with the highest home values are subject to mismeasurement associated with imputation. ACS data are subject to high standard errors.

Economic Growth						
Construct	**Measure (variable type)**	**Source(s)**	**Construction of Measure**	**Direction of Association**	**Notes and Justification**	**Limitations**
Rental market - prices	Change in median gross rent (continuous)	American Community Survey (DP04)	Median gross rent in 2015 – median gross rent in 2010 (adjusted 2015 dollars using CPI); Note: Median rents were top-coded at $2000 for 401 (9.1%) tracts in 2010. Median gross rent for these tracts were imputed (m=20) using interval regression for a continuous partially observed (censored) variable method.	Positive	Rise in rents also signal increased demand and in-migration and/or retention of residents with higher income who can afford the rents.	Median rents were top-coded at different values in different years. 2010 values were imputed for top-coded tracts to approximate true changes in median rents, and prevent the exclusion of 401 tracts from analyses. Tracts with the highest rents are subject to mismeasurement associated with imputation. ACS data are subject to high standard errors.

Economic Growth						
Construct	**Measure (variable type)**	**Source(s)**	**Construction of Measure**	**Direction of Association**	**Notes and Justification**	**Limitations**
Economic status of residents	Change in proportion of middle- to high-income residents	American Community Survey (C17002)	(Population with ratio of income to poverty level is 2.0 and over in 2015/population for whom poverty status Is determined in 2015)-(population with ratio of income to poverty level is 2.0 and over in 2010/population for whom poverty status Is determined in 2010)	Positive	Higher proportions of middle- to high-income residents indicate higher levels of spending in the neighborhood and economic growth.	ACS data are subject to high standard errors. Middle- to high-income residents might also spend a large percentage of their incomes outside the neighborhood if services and stores they prefer are not offered in the neighborhood.

Economic Growth						
Construct	**Measure (variable type)**	**Source(s)**	**Construction of Measure**	**Direction of Association**	**Notes and Justification**	**Limitations**
Investment	Change in mean dollar amount of loans originated for conventional home purchases	Home Mortgage Disclosure Act (HMDA) LAR	Recoded: (Total dollar amount of conventional home loans originated in 2015/total number conventional home loans originated in 2015)-(Total dollar amount of conventional home loans originated in 2010/total number of conventional home loans originated in 2010); 2010 dollar amounts adjusted to 2015 dollars using CPI; Variable top- and bottom-coded at 1st and 99th percentile.	Positive	Increases in mean amount of loans secured for home purchases indicate financial institutions' willingness to invest in a neighborhood as well as increased in home values.	Loan amounts do not fully represent home prices, as buyers will likely offer down payments. Change in mean dollar amount from 2010 to 2015 may less reliably measure change in home value if down payments (% of home price) are substantially different in both years. CORE logics transaction data and parcel data (not readily available at the time of the study) report sales prices.

Note: Measures in grey were not included in study.

Social and Cultural Shift						
Construct	**Measure (variable type)**	**Source(s)**	**Construction of Measure**	**Direction of Association**	**Notes and Justification**	**Limitations**
Social status of residents	Change in proportion adults (aged 25+) with a college degree	American Community Survey (B15002)	Recoded: (Adults aged 25+ with bachelor's degrees or higher in 2015/total population 25 years or older in 2015)-(Adults aged 25+ with bachelor's degrees or higher in 2010/total population 25 years or older in 2010)	Positive	Increases in the proportion of residents with college degrees signal a shift in social status within gentrified neighborhoods and possibly changes in norms and preferences.	ACS data are subject to high standard errors.
Demographic characteristics	Change in proportion of non-Hispanic White residents	American Community Survey (DP05)	Recoded: (Not Hispanic or Latino and White alone in 2015/total population in 2015)-(not Hispanic or Latino and White alone in 2010/total population in 2010)	Positive	Changes in the proportion of non-Hispanic White residents indicate social and cultural shifts.	ACS data are subject to high standard errors. Race/ethnicity is an imperfect measure of culture.

Social and Cultural Shift						
Construct	**Measure (variable type)**	**Source(s)**	**Construction of Measure**	**Direction of Association**	**Notes and Justification**	**Limitations**
Social status of residents	Change in proportion residents in management, business, science, and arts occupations	American Community Survey (S2401)	Recoded: (Employed civilians aged 16+ in management, business, science, and arts occupations in 2015/civilian employed population 16 years and older in 2015)-(employed civilians aged 16+ in management, business, science, and arts occupations in 2010/civilian employed population 16 years and older in 2010)	Positive	Increases in the proportion of residents in these occupations indicate increases in residents with higher occupational prestige and social shifts.	Margins of error were too high. Measure was highly correlated with education and income variables. Data on the job titles of residents are not available. Therefore, this is an imperfect measure for occupational prestige.
Demographic characteristics	Change in proportion residents aged 20-49 (continuous)	American Community Survey (S0101)	Recoded: Absolute[(Population aged 20-49 in 2015/total population in 2015)-(population aged 20-49 in 2010/total population in 2010)]	Positive	In-migrants to gentrified neighborhoods tend to be younger adults. Changes in the age composition of residents signal demographic and cultural/social shifts.	Margins of errors were too high, and it's unclear whether shifts in age composition will be observed within 5 years.

Social and Cultural Shift						
Construct	**Measure (variable type)**	**Source(s)**	**Construction of Measure**	**Direction of Association**	**Notes and Justification**	**Limitations**
Demographic characteristics	Change in proportion married or single households with no children	American Community Survey (B11004)	Recoded: Absolute[(Married or single families with no related children under 18 in 2015/total families in 2015)-(married or single families with no related children under 18 in 2010/total families in 2010)]	Positive	In-movers of gentrified neighborhoods are less likely to have children. Changes in the proportion of childless adults indicate changes in the types of families within the neighborhood and preferences.	Margins of errors were too high, and it's unclear whether shifts in age composition will be observed within 5 years.
Demand for retail services	Mix of establishments			Positive	New and different businesses are created to meet new and changing demand for goods and services. New establishments signal this shift.	Public data on the number and type of establishments are not available at the census tract level. Duns & Bradstreet has lists of new and closed businesses at the address level for a fee.

Social and Cultural Shift						
Construct	**Measure (variable type)**	**Source(s)**	**Construction of Measure**	**Direction of Association**	**Notes and Justification**	**Limitations**
Retail ownership	Small businesses			Unclear	Gentrified neighborhoods potentially attract more corporations and franchises (e.g., Starbucks, etc.) as well as small businesses that cater to niche demand for goods and services (e.g., boutique stores, etc.).	Public data on the number of small businesses are not available at the census tract level.

Note: Measures in grey were not included in study.

Table 2.2. Advantages and Disadvantages of Using Principal Components Analysis, K-Medians Cluster Analysis, and the Threshold Strategy for Identifying Upgraded Census Tracts

	Advantages	Disadvantages
Principal Components Analysis	• Can handle multiple indicators for each domain (higher reliability) • Summarizes indicators into optimally weighted sums • Allows correlation between components • PCA scores may be used to define types or pace of neighborhood upgrading	• Identification of components is subjective • Thresholds for classifying a neighborhood as upscaled are unclear • Components may be negatively correlated
K-Medians Cluster Analysis	• Can handle many indicators of neighborhood change • Method does not require assumptions, are driven by similarity or dissimilarity of observations • Method and algorithm are straightforward	• Indicators are not clustered into dimensions or components • Correlations between dimensions are not explored • Upgrading is not clear if groups are not distinct
Threshold Strategy	• Clearly defines gentrification as change in select indicators that outpaces average county changes • Concept of a gentrified neighborhood as tracts that experienced a rapid increase in rent as well as proportions of more affluent, educated, and White residents • Used and accepted by other researchers	• Relies on fewer indicators for each domain • All indicators of neighborhood change are given the same weight for identifying neighborhood upgrading • Correlations between dimensions are not explored • Neighborhoods are either gentrified or not gentrified (binary distribution)

Table 2.3. Neighborhood Change Categories by Strategy, Southern California Census Tracts, n=4,317

	PCA		K-Medians Cluster Analysis		Threshold Strategy	
	n	%	n	%	n	%
Low-income and gentrified	332	7.7	145	3.4	203	5
Low-income and not gentrified	1,043	24.2	1,230	28.5	1,172	27
Middle- to high-income and upscaled	791	18.3	642	14.9	224	5
Middle- to high-income and not upscaled	2,151	49.8	2,300	53.3	2,718	63

Sources: American Community Survey 2006-2010, 2011-2015 and Home Mortgage Disclosure Act Aggregate Tables 2010 and 2015

Table 2.4. Cross-tabulations of Neighborhood Change Categories by Strategy, Low-Income Southern California Census Tracts, n=1,375

Column Percent Row Percent		K-Medians Cluster Analysis		Threshold Strategy	
		Gentrified n=145	Not Gentrified n=1,230	Gentrified n=203	Not Gentrified n=1,172
Principal Components Analysis	Gentrified n=332	46.2 20.2	21.5 79.8	45.3 27.7	20.5 72.3
	Not Gentrified n=1,043	53.8 7.5	78.5 92.5	54.7 10.6	79.5 89.4
Threshold Strategy	Gentrified n=203	22.8 16.3	13.8 83.7		
	Not Gentrified n=1,172	77.2 9.6	86.2 90.4		

Sources: American Community Survey 2006-2010, 2011-2015 and Home Mortgage Disclosure Act Aggregate Tables 2010 and 2015

Table 2.5. Cross-tabulations of Neighborhood Change Categories by Strategy, Middle- to High-Income Southern California Census Tracts, n=2,942

Column Percent Row Percent		K-Medians Cluster Analysis		Threshold Strategy	
		Upscaled n=642	Not Upscaled n=2,300	Upscaled n=224	Not Upscaled n=2,718
Principal Components Analysis	Upscaled n=791	40.7 33.0	23.0 67.0	59.4 16.8	24.2 83.2
	Not Upscaled n=2,151	59.4 17.7	77.0 82.3	40.6 4.2	75.8 95.8
Threshold Strategy	Upscaled n=224	10.1 29.0	6.9 71.0		
	Not Upscaled n=2,718	89.9 21.2	93.1 78.8		

Sources: American Community Survey 2006-2010, 2011-2015 and Home Mortgage Disclosure Act Aggregate Tables 2010 and 2015

Table 2.6. Southern California Census Tracts Identified as Upscaled across Strategies, n=4,317

	n	%
None/Not Upscaled	2,557	59.2
PCA Only	644	14.9
Cluster Analysis Only	435	10.1
PCA & Cluster Analysis Only	254	5.9
Threshold Strategy Only	178	4.1
PCA & Threshold Strategy Only	151	3.5
All Strategies	74	1.7
Cluster Analysis & Threshold Strategy Only	24	0.6

Sources: American Community Survey 2006-2010, 2011-2015 and Home Mortgage Disclosure Act Aggregate Tables 2010 and 2015

Table 2.7. Phi Coefficients of Gentrified vs. Not Gentrified Tracts across Strategies, Southern California Counties, n=4,317

	PCA	K-Medians Cluster Analysis	Threshold Strategy
PCA	1		
K-Medians Cluster Analysis	.27	1	
Threshold Strategy	.31	.16	1

Sources: American Community Survey 2006-2010, 2011-2015 and Home Mortgage Disclosure Act Aggregate Tables 2010 and 2015

Supplemental Materials

Methods by County

Los Angeles County

Table 2.S1. Correlation Matrix of Indicators Used to Measure Neighborhood Upscaling, Los Angeles County Census Tracts, n=2,191

	Improvement loans per capita	Median HH income	Median home value	Mean home loan	Median rent	Percent middle income	Percent BA/BA or more	Percent NH White
Improvement loans per capita	1							
Median HH income	0.09	1						
Median home value	0.35	0.02	1					
Mean home loan	0.33	0.01	0.23	1				
Median rent	0.04	0.07	0.05	0.07	1			
Percent middle income	0.06	0.42	0.04	0.03	0.08	1		
Percent BA/BA or more	0.05	0.16	0.04	0.04	0.06	0.19	1	
Percent NH White	-0.08	0.09	-0.03	-0.01	0.03	0.09	0.12	1

Sources: American Community Survey 2006-2010, 2011-2015 and Home Mortgage Disclosure Act Aggregate Tables 2010 and 2015

Table 2.S2. Principal Components Analysis Results, Los Angeles County, n=2,191

	Component 1	Component 2	Unexplained
Eigenvalue	1.74	1.50	
Variance	1.63	1.61	
Proportion	0.20	0.20	
Rotated Components			
Improvement loans per capita	0.61	0.03	0.39
Median HH income	0.01	0.59	0.44
Median home value	0.55	0.00	0.51
Mean home loan	0.54	0.00	0.53
Median rent	0.11	0.19	0.92
Percent middle income	0.01	0.60	0.42
Percent BA/BA or more	0.03	0.42	0.72
Percent NH White	0.16	0.29	0.83

Sources: American Community Survey 2006-2010, 2011-2015 and Home Mortgage Disclosure Act Aggregate Tables 2010 and 2015

Table 2.S3. Summary (Mean and Median) of Indicators Used to Measure Neighborhood Upscaling* by K-Medians Cluster, Los Angeles County Census Tracts, n=2,191

	Group 1 n=1,084		Group 2 n=933		Group 3 n=174	
	Mean	**Median**	**Mean**	**Median**	**Mean**	**Median**
Change in dollar amount of improvement loans per capita	$96	$61	$185	$95	$1,062	$513
Change in median household income	-$5,214	-$4,920	-$4,237	-$4,107	-$2,762	-$636
Change in median home value	-$97,212	-$101,084	-$108,100	-$105,669	$35,527	$17,874
Change in mean dollar amount of loans originated for conventional home purchases	$13,792	$31,147	$133,268	$120,617	$518,834	$380,640
Change in median gross rent	19.6	0.7	39.7	21.9	128.8	77.8
Change in proportion of middle- to high-income residents	-3.4	-3.6	-2.8	-2.8	-0.9	-1.0
Change in proportion of adults (aged 25+) with a college degree	1.2	1.2	1.6	1.2	3.2	3.4
Change in proportion of non-Hispanic White residents	-2.0	-1.2	-1.0	-0.5	-2.0	-1.1

Sources: American Community Survey 2006-2010, 2011-2015 and Home Mortgage Disclosure Act Aggregate Tables 2010 and 2015

* Census tracts in Group 1 were categorized as upscaled.

Orange County

Table 2.S4. Correlation Matrix of Indicators Used to Measure Neighborhood Upscaling, Orange County Census Tracts, n=567

	Improvement loans per capita	Median HH income	Median home value	Mean home loan	Median rent	Percent middle income	Percent BA/BA or more	Percent NH White
Improvement loans per capita	1							
Median HH income	-0.04	1						
Median home value	0.40	-0.02	1					
Mean home loan	0.04	0.00	0.18	1				
Median rent	0.00	0.12	0.03	0.06	1			
Percent middle income	0.07	0.38	0.00	-0.02	0.10	1		
Percent BA/BA or more	0.09	0.23	0.01	-0.01	0.04	0.17	1	
Percent NH White	0.06	0.04	-0.02	0.04	-0.05	0.12	0.08	1

Sources: American Community Survey 2006-2010, 2011-2015 and Home Mortgage Disclosure Act Aggregate Tables 2010 and 2015

Table 2.S5. Principal Components Analysis Results, Orange County, n=567

	Component 1	Component 2	Component 3	Unexplained
Eigenvalue	1.61	1.46	1.08	
Variance	1.62	1.47	1.11	
Proportion	0.20	0.18	0.14	
Rotated Components				
Improvement loans per capita	0.02	0.65	-0.17	0.35
Median HH income	0.61	-0.09	0.20	0.39
Median home value	-0.06	0.68	0.10	0.31
Mean home loan	-0.03	0.30	0.35	0.72
Median rent	0.22	0.01	0.71	0.42
Percent middle income	0.60	0.01	0.04	0.44
Percent BA/BA or more	0.44	0.07	-0.12	0.64
Percent NH White	0.19	0.10	-0.54	0.58

Sources: American Community Survey 2006-2010, 2011-2015 and Home Mortgage Disclosure Act Aggregate Tables 2010 and 2015

Table 2.S6. Summary (Mean and Median) of Indicators Used to Measure Neighborhood Upscaling* by K-Medians Cluster, Orange County Census Tracts, n=567

	Group 1 n=161		Group 2 n=116		Group 3 n=290	
	Mean	**Median**	**Mean**	**Median**	**Mean**	**Median**
Change in dollar amount of improvement loans per capita	$644	$450	-$145	-$99	$95	$80
Change in median household income	-$6,012	-$5,074	-$5,554	-$4,655	-$4,895	-$5,042
Change in median home value	-$74,953	-$96,971	-$112,046	-$109,003	-$98,792	-$95,902
Change in mean dollar amount of loans originated for conventional home purchases	$101,159	$91,081	$88,282	$80,231	$65,127	$67,972
Change in median gross rent	$13	-$7	$83	$10	$4	-$29
Change in proportion of middle- to high-income residents	-2.3	-1.7	-3.2	-2.9	-4.1	-3.4
Change in proportion of adults (aged 25+) with a college degree	2.3	2.5	1.4	1.0	1.2	1.1
Change in proportion of non-Hispanic White residents	-3.0	-3.0	-4.3	-3.1	-3.2	-2.6

Sources: American Community Survey 2006-2010, 2011-2015 and Home Mortgage Disclosure Act Aggregate Tables 2010 and 2015

* Census tracts in Group 1 were categorized as upscaled.

San Bernardino County

Table 2.S7. Correlation Matrix of Indicators Used to Measure Neighborhood Upscaling, San Bernardino County Census Tracts, n=356

	Improvement loans per capita	Median HH income	Median home value	Mean home loan	Median rent	Percent middle income	Percent BA/BA or more	Percent NH White
Improvement loans per capita	1							
Median HH income	-0.10	1						
Median home value	-0.22	0.13	1					
Mean home loan	0.22	0.01	-0.02	1				
Median rent	-0.04	0.09	0.04	0.00	1			
Percent middle income	0.14	0.43	0.04	0.09	0.04	1		
Percent BA/BA or more	-0.05	0.18	0.12	0.05	0.04	0.17	1	
Percent NH White	-0.01	-0.02	-0.09	0.01	0.01	0.04	0.01	1

Sources: American Community Survey 2006-2010, 2011-2015 and Home Mortgage Disclosure Act Aggregate Tables 2010 and 2015

Table 2.S8. Principal Components Analysis Results, San Bernardino County, n=356

	Component 1	Component 2	Component 3	Unexplained
Eigenvalue	1.62	1.37	1.04	
Variance	1.63	1.37	1.07	
Proportion	0.20	0.17	0.13	
Rotated Components				
Improvement loans per capita	0.04	0.70	-0.02	0.34
Median HH income	0.61	-0.08	0.03	0.38
Median home value	0.16	-0.37	-0.44	0.48
Mean home loan	0.16	0.54	-0.21	0.56
Median rent	0.18	-0.15	0.23	0.87
Percent middle income	0.63	0.23	0.11	0.34
Percent BA/BA or more	0.39	-0.06	-0.07	0.72
Percent NH White	0.10	-0.08	0.84	0.27

Sources: American Community Survey 2006-2010, 2011-2015 and Home Mortgage Disclosure Act Aggregate Tables 2010 and 2015

Table 2.S9. Summary (Mean and Median) of Indicators Used to Measure Neighborhood Upscaling* by K-Medians Cluster, San Bernardino County Census Tracts, n=356

	Group 1 n=91		Group 2 n=111		Group 3 n=154	
	Mean	**Median**	**Mean**	**Median**	**Mean**	**Median**
Change in dollar amount of improvement loans per capita	$120	$102	$97	$71	$198	$155
Change in median household income	-$4,777	-$5,239	-$7,640	-$7,099	-$10,727	-$10,134
Change in median home value	-$49,569	-$61,806	-$106,903	-$105,075	-$134,382	-$129,549
Change in mean dollar amount of loans originated for conventional home purchases	$63,186	$54,281	-$8,156	$502	$69,574	$65,301
Change in median gross rent	-$29	-$46	-$63	-$64	-$44	-$60
Change in proportion of middle- to high-income residents	-4.1	-3.3	-7.7	-7.6	-6.4	-6.1
Change in proportion of adults (aged 25+) with a college degree	1.6	1.7	-0.5	-0.5	0.7	0.7
Change in proportion of non-Hispanic White residents	-3.8	-3.8	-3.5	-3.2	-3.2	-3.3

Sources: American Community Survey 2006-2010, 2011-2015 and Home Mortgage Disclosure Act Aggregate Tables 2010 and 2015

* Census tracts in Group 1 were categorized as upscaled.

Riverside County

Table 2.S10. Correlation Matrix of Indicators Used to Measure Neighborhood Upscaling, Riverside County Census Tracts, n=441

	Improvement loans per capita	Median HH income	Median home value	Mean home loan	Median rent	Percent middle income	Percent BA/BA or more	Percent NH White
Improvement loans per capita	1							
Median HH income	-0.02	1						
Median home value	-0.09	0.13	1					
Mean home loan	0.23	-0.06	-0.15	1				
Median rent	0.04	0.19	0.08	-0.02	1			
Percent middle income	0.10	0.46	0.02	-0.05	0.15	1		
Percent BA/BA or more	0.06	0.17	0.07	0.05	0.15	0.13	1	
Percent NH White	0.14	-0.02	-0.03	0.14	-0.02	0.15	0.06	1

Sources: American Community Survey 2006-2010, 2011-2015 and Home Mortgage Disclosure Act Aggregate Tables 2010 and 2015

Table 2.S11. Principal Components Analysis Results, Riverside County, n=441

	Component 1	Component 2	Unexplained
Eigenvalue	1.71	1.44	
Variance	1.71	1.44	
Proportion	0.21	0.18	
Rotated Components			
Improvement loans per capita	0.08	0.56	0.54
Median HH income	0.59	-0.10	0.39
Median home value	0.21	-0.35	0.75
Mean home loan	-0.09	0.57	0.52
Median rent	0.38	-0.03	0.76
Percent middle income	0.57	0.10	0.44
Percent BA/BA or more	0.35	0.13	0.77
Percent NH White	0.11	0.45	0.69

Sources: American Community Survey 2006-2010, 2011-2015 and Home Mortgage Disclosure Act Aggregate Tables 2010 and 2015

Table 2.S12. Summary (Mean and Median) of Indicators Used to Measure Neighborhood Upscaling* by K-Medians Cluster, Riverside County Census Tracts, n=441

	Group 1 n=80		Group 2 n=199		Group 3 n=162	
	Mean	**Median**	**Mean**	**Median**	**Mean**	**Median**
Change in dollar amount of improvement loans per capita	$544	$485	$52	$55	$235	$226
Change in median household income	-$9,544	-$9,564	-$6,805	-$5,709	-$7,057	-$7,030
Change in median home value	-$111,047	-$113,689	-$98,629	-$93,457	-$112,710	-$106,296
Change in mean dollar amount of loans originated for conventional home purchases	$75,831	$68,411	$34,722	$32,033	$52,254	$52,469
Change in median gross rent	-$50	-$47	-$63	-$43	-$41	-$38
Change in proportion of middle- to high-income residents	-3.5	-3.2	-6.0	-6.5	-5.1	-5.5
Change in proportion of adults (aged 25+) with a college degree	0.9	1.0	0.3	0.6	-0.5	-0.1
Change in proportion of non-Hispanic White residents	-2.2	-2.1	-3.9	-3.8	-3.1	-2.9

Sources: American Community Survey 2006-2010, 2011-2015 and Home Mortgage Disclosure Act Aggregate Tables 2010 and 2015

* Census tracts in Group 1 were categorized as upscaled.

San Diego County

Table 2.S13. Correlation Matrix of Indicators Used to Measure Neighborhood Upscaling, San Diego County Census Tracts, n=599

	Improvement loans per capita	Median HH income	Median home value	Mean home loan	Median rent	Percent middle income	Percent BA/BA or more	Percent NH White
Improvement loans per capita	1							
Median HH income	-0.07	1						
Median home value	0.19	-0.07	1					
Mean home loan	0.23	-0.02	0.17	1				
Median rent	0.10	0.09	0.01	0.12	1			
Percent middle income	0.001	0.45	-0.02	0.04	0.07	1		
Percent BA/BA or more	0.07	0.23	0.08	0.09	0.03	0.24	1	
Percent NH White	-0.01	0.03	-0.01	0.01	-0.004	0.11	0.13	1

Sources: American Community Survey 2006-2010, 2011-2015 and Home Mortgage Disclosure Act Aggregate Tables 2010 and 2015

Table 2.S14. Principal Components Analysis Results, San Diego County, n=599

	Component 1	Component 2	Component 3	Unexplained
Eigenvalue	1.69	1.46	1.04	
Variance	1.66	1.49	1.07	
Proportion	0.21	0.19	0.13	
Rotated Components				
Improvement loans per capita	-0.08	0.58	-0.10	0.51
Median HH income	0.64	-0.15	-0.11	0.33
Median home value	-0.14	0.51	0.16	0.58
Mean home loan	0.01	0.55	-0.13	0.54
Median rent	0.24	0.22	-0.61	0.48
Percent middle income	0.61	-0.03	0.03	0.37
Percent BA/BA or more	0.37	0.20	0.34	0.51
Percent NH White	0.09	0.04	0.67	0.48

Sources: American Community Survey 2006-2010, 2011-2015 and Home Mortgage Disclosure Act Aggregate Tables 2010 and 2015

Table 2.S15. Summary (Mean and Median) of Indicators Used to Measure Neighborhood Upscaling* by K-Medians Cluster, San Diego County Census Tracts, n=599

	Group 1 n=419		Group 2 n=180	
	Mean	**Median**	**Mean**	**Median**
Change in dollar amount of improvement loans per capita	$65	$73	$582	$428
Change in median household income	-$4,219	-$3,932	-$3,680	-$3,747
Change in median home value	-$93,903	-$93,917	-$89,242	-$92,561
Change in mean dollar amount of loans originated for conventional home purchases	$56,947	$52,041	$93,216	$73,091
Change in median gross rent	$5	-$20	$61	$10
Change in proportion of middle- to high-income residents	-2.9	-3.1	-2.6	-2.4
Change in proportion of adults (aged 25+) with a college degree	1.4	1.4	2.4	2.2
Change in proportion of non-Hispanic White residents	-2.4	-1.7	-3.0	-2.9

Sources: American Community Survey 2006-2010, 2011-2015 and Home Mortgage Disclosure Act Aggregate Tables 2010 and 2015

* Census tracts in Group 2 were categorized as upscaled.

Ventura County

Table 2.S16. Correlation Matrix of Indicators Used to Measure Neighborhood Upscaling, Ventura County Census Tracts, n=163

	Improvement loans per capita	Median HH income	Median home value	Mean home loan	Median rent	Percent middle income	Percent BA/BA or more	Percent NH White
Improvement loans per capita	1							
Median HH income	-0.10	1						
Median home value	0.23	0.21	1					
Mean home loan	-0.06	0.01	-0.12	1				
Median rent	0.13	0.14	0.14	-0.06	1			
Percent middle income	0.04	0.38	0.01	0.01	0.02	1		
Percent BA/BA or more	-0.16	0.21	0.01	0.044	0.03	0.10	1	
Percent NH White	-0.11	0.25	0.09	0.21	-0.003	0.17	0.17	1

Sources: American Community Survey 2006-2010, 2011-2015 and Home Mortgage Disclosure Act Aggregate Tables 2010 and 2015

Table 2.S17. Principal Components Analysis Results, Ventura County, n=163

	Component 1	Component 2	Component 3	Unexplained
Eigenvalue	1.75	1.44	1.03	
Variance	1.73	1.34	1.17	
Proportion	0.22	0.17	0.15	
Rotated Components				
Improvement loans per capita	-0.14	0.70	0.09	0.36
Median HH income	0.62	-0.01	-0.04	0.35
Median home value	0.23	0.53	-0.07	0.48
Mean home loan	-0.06	0.04	0.82	0.24
Median rent	0.19	0.33	-0.19	0.71
Percent middle income	0.47	0.00	0.04	0.62
Percent BA/BA or more	0.41	-0.35	-0.10	0.59
Percent NH White	0.36	0.02	0.52	0.43

Sources: American Community Survey 2006-2010, 2011-2015 and Home Mortgage Disclosure Act Aggregate Tables 2010 and 2015

Table 2.S18. Summary (Mean and Median) of Indicators Used to Measure Neighborhood Upscaling* by K-Medians Cluster, Ventura County Census Tracts, n=163

	Group 1 n=101		Group 2 n=62	
	Mean	**Median**	**Mean**	**Median**
Change in dollar amount of improvement loans per capita	$135	$99	$129	$90
Change in median household income	-$3,139	-$3,276	-$6,961	-$6,487
Change in median home value	-$115,316	-$120,235	-$166,433	-$157,979
Change in mean dollar amount of loans originated for conventional home purchases	$11,102	$29,142	$117,942	$98,499
Change in median gross rent	$44	-$12	-$17	-$34
Change in proportion of middle- to high-income residents	-3.3	-2.0	-3.7	-3.5
Change in proportion of adults (aged 25+) with a college degree	1.4	1.7	0.3	-0.4
Change in proportion of non-Hispanic White residents	-2.6	-2.1	-3.4	-3.3

Sources: American Community Survey 2006-2010, 2011-2015 and Home Mortgage Disclosure Act Aggregate Tables 2010 and 2015

* Census tracts in Group 1 were categorized as upscaled.

Results by County

Los Angeles County

Home to approximately 10 million people, Los Angeles (LA) County is the most populous county in the United States. The majority of residents are people of color. Nearly half (48%) of residents in 2011-2015 were Latina or Hispanic, 27% were non-Hispanic White, 14% were non-Hispanic Asian, 8% were non-Hispanic Black, and 5% were Native Hawaiian or Pacific Islander, American Indian or Alaska Native, identified some other race, or identified two or more races. Median income for the county was $56,200, but median income ranged from $9,500 to $265,900 across census tracts within the county in 2006-2010. At the start of the study period, 2006-2010, census tracts in LA County on average housed 4,300 residents, roughly 1,400 households. The number of housing units in each tract ranged from 158 to 7,200 units; the mean was 1,500. The vacancy rate was nearly 6%.

Between 2006-2010 and 2011-2015, median rents increased an average of $36, median housing values fell $92,100, and real median household incomes decreased $4,600. Mean home loan amounts increased approximately $104,800 and home improvement loans per resident increased an average $211.

Table 2.S19. Summary Statistics of Indicators Used to Measure Neighborhood Upscaled, Los Angeles County Census Tracts, n=2,191

	Mean	SD	Min	Max
Change in dollar amount of improvement loans per capita	210.9	598.2	-2139.5	9609.5
Change in median household income	-4603.2	12196.7	-113484.5	74954.7
Change in median home value	-92091.7	91094.9	-661557.3	717825.6
Change in mean dollar amount of loans originated for conventional home purchases	104777.3	218401.6	-796947.0	6068723.0
Change in median gross rent	36.1	267.4	-1337.8	2112.4
Change in proportion of middle- to high-income residents	-3.0	8.6	-41.3	28.7
Change in proportion of adults (aged 25+) with a college degree	1.5	5.8	-20.7	29.2
Change in proportion of non-Hispanic White residents	-1.6	5.9	-31.6	22.5

Sources: American Community Survey 2006-2010, 2011-2015 and Home Mortgage Disclosure Act Aggregate Tables 2010 and 2015

The three strategies generated a wide range of LA census tracts that "upscaled" between 2006-2010 and 2011-2015. Using principal components analysis, 651 of 2,191 (29.7%) were considered upscaled. The threshold strategy identified 245 (11.2%) upscaled tracts, and k-medians cluster analysis identified the fewest upscaled tracts, 174 (7.9%). By definition, upscaled tracts using the threshold strategy had greater increases in household income, rent, college-educated residents, and non-Hispanic White residents compared to increases at the county level. Mean increases in these indicators were greater for the 245 upscaled tracts using the threshold strategy compared to upscaled tracts using PCA or K-medians cluster analysis. In contrast, increases in improvement loans per resident were greater among upscaled tracts using PCA and K-medians cluster analysis. Median home values also did not fall as steeply among these tracts compared to upscaled tracts under the threshold strategy. Notably, upscaled tracts identified under threshold strategy on average underwent increases in the proportion of non-Hispanic White residents, whereas upscaled tracts using PCA and K-medians cluster analysis on average experienced decreases.

Table 2.S20. Summary Statistics of Indicators for Upscaled and Not Upscaled Neighborhoods by Strategy, Los Angeles County Census Tracts, n=2,191

	PCA		K-Medians Cluster Analysis		Threshold Strategy	
Upscaled	**n=651**		**n=174**		**n=245**	
Change in…	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Improvement loans per capita	401.0	877.0	1062.1	1672.9	213.4	687.7
Median household income	$3,289	$10,542	-$2,762	$23,640	$5,004	$8,819
Median home value	-$49,927	$101,896	$35,527	$163,134	-$86,113	$97,883
Mean dollar amount of home loans	$170,623	$308,460	$518,834	$569,801	$133,161	$240,163
Median gross rent	$127	$331	$129	$336	$170	$256
Proportion of middle- to high-income residents	2.9	6.3	-0.9	6.3	2.1	8.1
Proportion of adults (aged	4.0	6.1	3.2	6.8	6.5	4.7

	PCA		K-Medians Cluster Analysis		Threshold Strategy	
25+) with a college degree						
Proportion of non-Hispanic White residents	-1.2	6.0	-2.0	6.7	3.2	4.4
Not Upscaled	**n=1540**		**n=2017**		**n=1946**	
Change in…	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Improvement loans per capita	130.6	403.3	137.5	284.0	210.6	586.2
Median household income	-$7,939	$11,281	-$4,762	$10,645	-$5,813	$12,027
Median home value	-$108,799	$81,426	-$102,248	$73,510	-$91,960	$91,244
Mean dollar amount of home loans	$76,942	$158,370	$69,058	$88,776	$101,204	$215,308
Median gross rent	-$1	$228	$29	$261	$20	$266
Proportion of middle- to high-income residents	-5.4	8.3	-3.1	8.8	-3.6	8.5
Proportion of adults (aged 25+) with a college degree	0.5	5.4	1.4	5.7	0.9	5.6
Proportion of non-Hispanic White residents	-1.8	5.8	-1.6	5.8	-2.2	5.7

Upscaled census tracts that were categorized as low-income in 2006-2010 were considered gentrified by 2011-2015. Between 2% and 10% of neighborhoods or census tracts in LA County gentrified during the study period.

Table 2.S21. Neighborhood Change Categories by Strategy, Los Angeles County Census Tracts, n=2,191

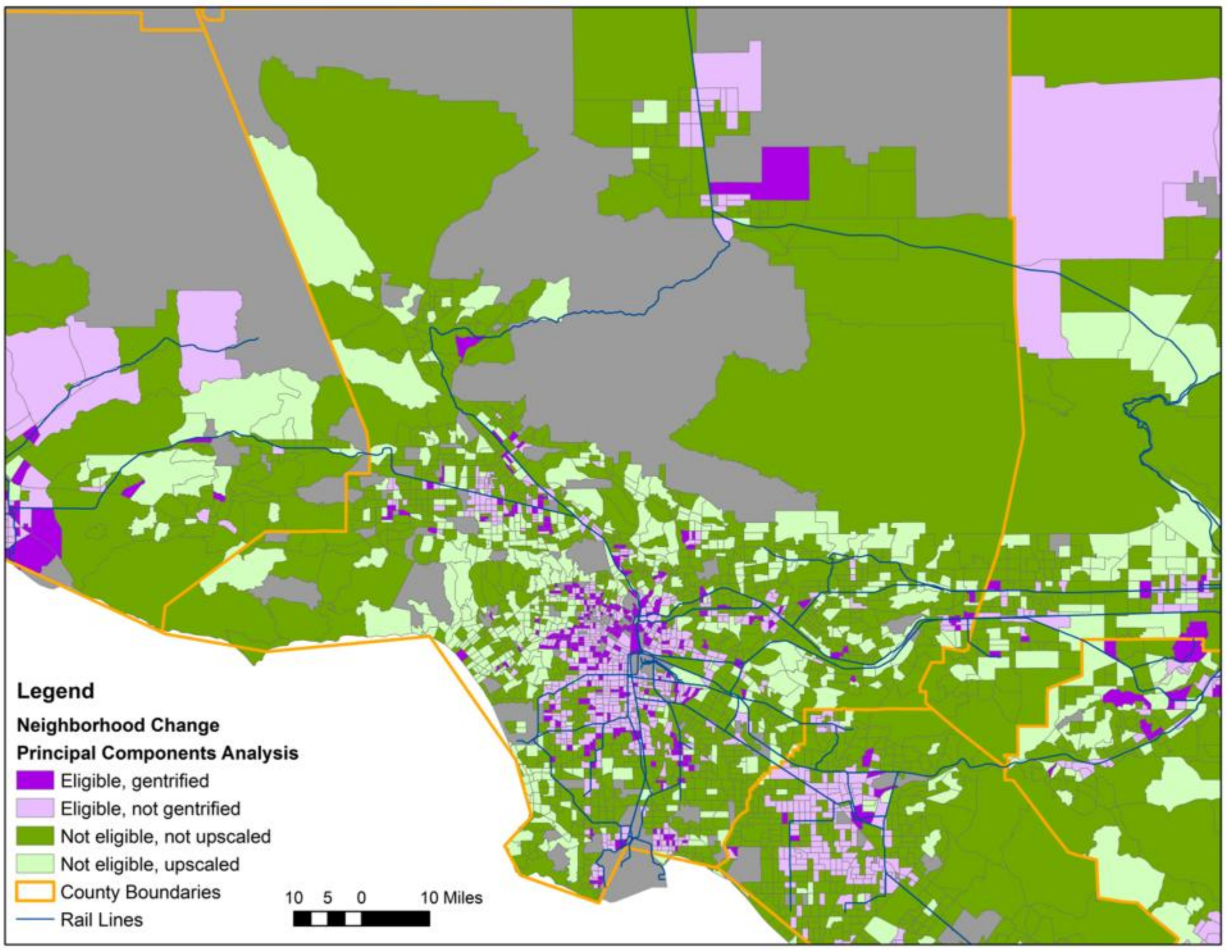
	PCA		K-Medians Cluster Analysis		Threshold Strategy	
	n	**%**	**n**	**%**	**n**	**%**
Low-income and gentrified	209	9.5	42	1.9	131	6
Low-income and not gentrified	529	24.1	696	31.8	607	27.7
Middle- to high-income and upscaled	441	20.1	132	6	114	5.2
Middle- to high-income and not upscaled	1,012	46.2	1,321	60.3	1,339	61.1

Phi coefficients suggest small to moderate positive associations between census tracts identified as gentrified using one strategy compared to another. The association is weakest between results using K-medians cluster analysis and the threshold strategy (phi=.22).

Table 2.S22. Phi Coefficients of Gentrified vs. Not Gentrified Tracts across Strategies, Los Angeles County, n=2,191

	PCA	K-Medians Cluster Analysis	Threshold Strategy
PCA	1		
K-Medians Cluster Analysis	.34	1	
Threshold Strategy	.33	0.22	1

Figure 2.S1. Map of Neighborhood Change, Census Tracts in Los Angeles County



Note: Eligible tracts had median household incomes that were <80% of the median household income for their respective counties.

Orange County

An average of 3.1 million people lived in Orange County between 2011 and 2015. Non-Hispanic White residents represent the largest racial/ethnic group in the county at 42%, followed by Latina (34%) and Asian (19%) residents. Compared to other counties in Southern California, Orange County had the greatest median income ($76,500). Within the county, median incomes ranged from $22,600 to greater than $221,700 across census tracts. The average number of housing units in each census tract was 1,810; mean vacancy rate was 5.2%.

On average, median household income and the proportion of middle- to high-income residents in Orange County census tracts fell between 2006-2010 and 2011-2015. Median home values declined an average of $94,500 during this period, and median gross rent increased an average of $18 across all census tracts. During this period, the dollar amount of home improvement loans per resident also increased an average of $202, as did the average dollar amount of home homes. The proportion of non-Hispanic White residents in each tract decreased an average of 3.3 percentage points.

Table 2.S23. Summary Statistics of Indicators Used to Measure Neighborhood Upscaling, Orange County Census Tracts, n=567

	Mean	SD	Min	Max
Change in dollar amount of improvement loans per capita	$202	$414	-$664	$3,803
Change in median household income	-$5,347	$12,758	-$89,277	$36,480
Change in median home value	-$94,527	$80,821	-$293,559	$392,077
Change in mean dollar amount of loans originated for conventional home purchases	$80,095	$213,063	-$4,220,669	$1,120,017
Change in median gross rent	$18	$252	-$1,140	$1,232
Change in proportion of middle- to high-income residents	-3.4	7.0	-24.5	14.7
Change in proportion of adults (aged 25+) with a college degree	1.6	5.4	-18.1	23.4
Change in proportion of non-Hispanic White residents	-3.3	6.4	-25.7	16.5

Sources: American Community Survey 2006-2010, 2011-2015 and Home Mortgage Disclosure Act Aggregate Tables 2010 and 2015

K-medians cluster analysis identified 161 upscaled census tracts, which was a far greater number compared to principal components analysis (n=61) and threshold strategy (n=48) results. Compared to upscaled tracts using the other two strategies, upscaled tracts identified through K-medians cluster analysis had greater average increase in dollar amounts of home improvement ($644) and the greatest mean decrease in median household incomes ($6,000). Principal components analysis identified 61 census tracts in Orange County that upscaled during the study period. These neighborhoods experienced greatest average increases in median gross rent ($220) and size of home purchase loans ($147,000). Although median home values on average declined for upscaled tracts across all strategies, mean decline median home values was most modest among upscaled tracts using PCA (-$14,400). The proportion of non-Hispanic White residents in upscaled census tracts using PCA also dropped an average of nearly 6 percentage points.

In contrast, the 48 census tracts categorized as upscaled using the threshold strategy on average had a 2 percentage point increase in percent of non-Hispanic White residents and 6 percentage point increase in the proportion of residents with Bachelor's degrees. Median gross rent also increased an average $143 among these neighborhoods, but home values fell an average $94,100.

Table 2.S24. Summary Statistics of Indicators for Upscaled and Not Upscaled Neighborhoods by Strategy, Orange County Census Tracts, n=567

	PCA		K-Medians Cluster Analysis		Threshold Strategy	
Upscaled	**n=61**		**n=161**		**n=48**	
Change in…	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Improvement loans per capita	$407	$543	$644	$529	$209	$507
Median household income	$3,184	$9,300	-$6,012	$16,260	$5,133	$6,883
Median home value	-$14,437	$125,282	-$74,953	$107,472	-$93,067	$60,672
Mean dollar amount of home loans	$147,043	$181,857	$101,159	$382,929	$74,284	$76,447
Median gross rent	$220	$335	$13	$327	$143	$177
Proportion of middle- to high-income residents	-0.2	4.5	-2.3	6.0	0.1	7.1

	PCA		K-Medians Cluster Analysis		Threshold Strategy	
Proportion of adults (aged 25+) with a college degree	2.2	4.4	2.3	5.9	6.1	3.3
Proportion of non-Hispanic White residents	-5.8	5.1	-3.0	6.5	2.2	3.5
Not Upscaled	**n=506**		**n=406**		**n=519**	
Change in…	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Improvement loans per capita	$177	$390	$26	$144	$201	$405
Median household income	-$6,375	$12,739	-$5,083	$11,080	-$6,316	$12,744
Median home value	-$104,414	$65,411	-$102,578	$62,994	-$94,889	$80,658
Mean dollar amount of home loans	$72,025	$215,275	$71,743	$72,568	$80,633	$221,515
Median gross rent	-$1	$236	$26	$225	$11	$261
Proportion of middle- to high-income residents	-3.8	7.1	-3.8	7.3	-3.7	6.9
Proportion of adults (aged 25+) with a college degree	1.5	5.5	1.3	5.2	1.2	5.4
Proportion of non-Hispanic White residents	-3.0	6.4	-3.5	6.3	-3.9	6.3

At most, 3 percent of Orange County census tracts gentrified between 2006-2010 and 2011-2015.

Table 2.S25. Neighborhood Change Categories by Strategy, Orange County Census Tracts, n=567

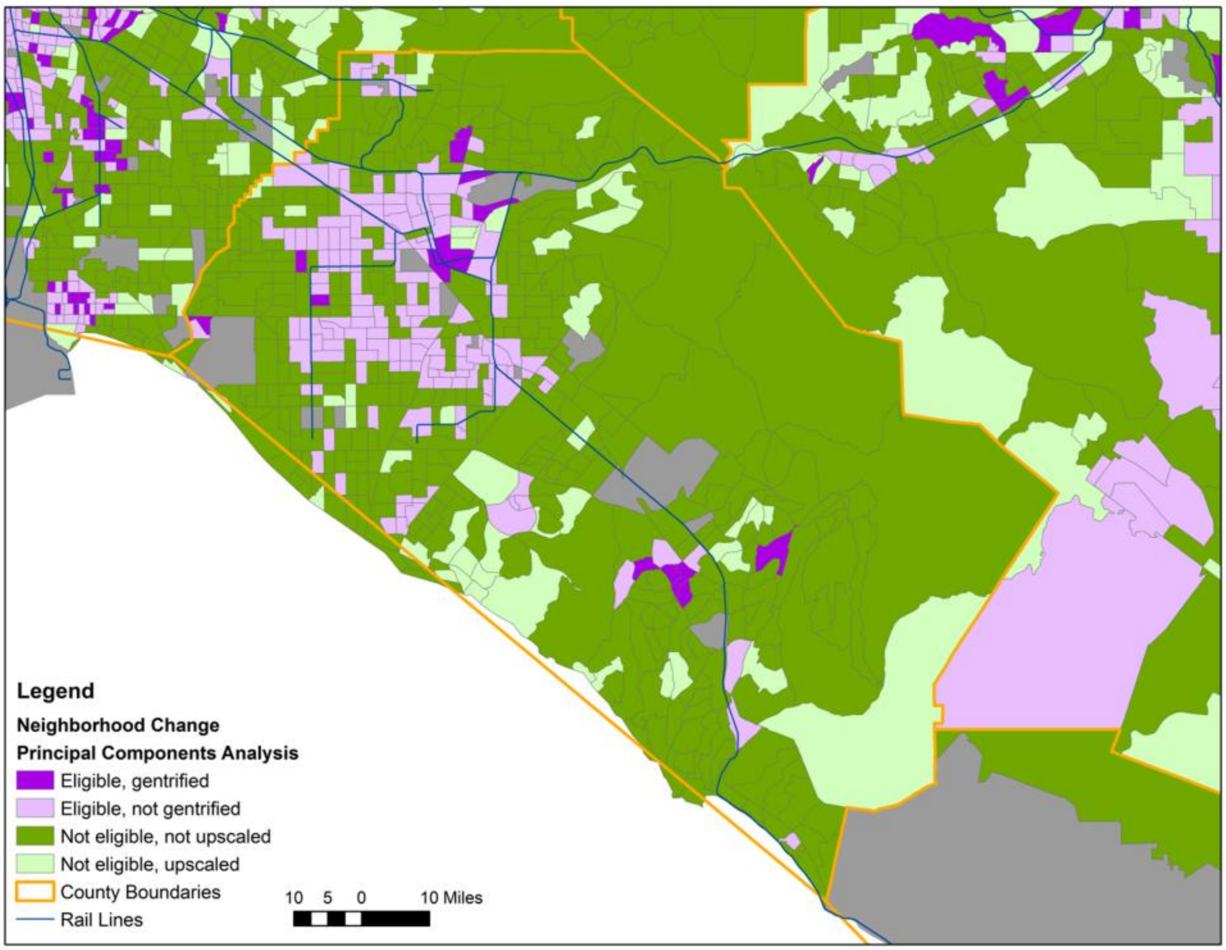
	PCA		K-Medians Cluster Analysis		Threshold Strategy	
	n	**%**	**n**	**%**	**n**	**%**
Low-income and gentrified	15	2.6	14	2.5	11	1.9
Low-income and not gentrified	141	24.9	142	25	145	25.6
Middle- to high-income and upscaled	46	8.1	147	25.9	37	6.5
Middle- to high-income and not upscaled	365	64.4	264	46.6	374	66

Despite the small number of census tracts classified as gentrified, there was little to no association between gentrified tracts across the three strategies. In other words, each strategy identified a nearly different set of gentrified census tracts.

Table 2.S26. Phi Coefficients of Gentrified vs. Not Gentrified Tracts across Strategies, Orange County, n=567

	PCA	K-Medians Cluster Analysis	Threshold Strategy
PCA	1		
K-Medians Cluster Analysis	.19	1	
Threshold Strategy	.02	.06	1

Figure 2.S2. Map of Neighborhood Change, Census Tracts in Orange County



Note: Eligible tracts had median household incomes that were <80% of the median household income for their respective counties.

San Bernardino County

San Bernardino County had less than 2.1 million residents in 2011-2015 and is the least populous county in our study area. It also had the lowest median income ($53,400). Half (51%) of San Bernardino County's residents identified as Latino or Hispanic, and nearly a third (31%) of residents were non-Hispanic White. The third largest racial/ethnic group in this county are non-Hispanic Black residents (8%). In 2006-2010, census tracts in San Bernardino had an average of 1,890 housing units. Mean vacancy rate was high at 11.6%.

Over the next five years (2011-2015), median home values fell sharply by an average of $104,100. Median gross rents also dropped an average of $46. Real median household income declined $8,200 across all tracts, which was mirrored by an average decrease in the proportion of residents with middle- to high-incomes (above 200% of federal poverty level thresholds) by 6.2 percentage points.

Table 2.S27. Summary Statistics of Indicators Used to Measure Neighborhood Upscaling, San Bernardino County Census Tracts, n=356

	Mean	SD	Min	Max
Change in dollar amount of improvement loans per capita	$146	$156	-$553	$1,128
Change in median household income	-$8,244	$9,564	-$40,713	$24,908
Change in median home value	-$104,134	$49,109	-$248,941	$148,525
Change in mean dollar amount of loans originated for conventional home purchases	$43,705	$51,698	-$139,572	$454,999
Change in median gross rent	-$46	$276	-$798	$2,320
Change in proportion of middle- to high-income residents	-6.2	9.1	-30.6	25.2
Change in proportion of adults (aged 25+) with a college degree	0.6	4.8	-16.0	17.5
Change in proportion of non-Hispanic White residents	-3.5	6.3	-23.8	16.3

Sources: American Community Survey 2006-2010, 2011-2015 and Home Mortgage Disclosure Act Aggregate Tables 2010 and 2015

There was a large discrepancy in the numbers of upscaled census tracts identified by principal components analysis and k-medians cluster analysis compared to using the threshold strategy. PCA results generated 81 census tracts that upscaled during the study period. These tracts had the greatest mean increase in average home purchase loan amount ($76,000). Median home values also declined most sharply, an average of -$117,000. On average, upscaled tracts using PCA had decreases in median household incomes, median rents, and the proportion of non-Hispanic White residents. K-medians cluster analysis identified 91 upscaled census tracts. These tracts on average had greater declines in median household income, percent of middle- to high-income residents, and percent of non-Hispanic White residents than upscaled tracts using other strategies.

Only 28 tracts met the criteria for upscaling under the threshold strategy. Unlike tracts categorized as upscaled using PCA or k-medians cluster analysis, median gross rent for these 28 tracts increased an average $111. Median household income decreased (-$410) but not as prominently as upscaled tracts using other strategies. Increases in the average dollar amount of home purchase loans were also more moderate, but the proportion of residents with Bachelor's degrees increased an average of 4.5 percentage points compared to roughly 2 percentage points using other strategies.

Table 2.S28. Summary Statistics of Indicators for Upscaled and Not Upscaled Neighborhoods by Strategy, San Bernardino County Census Tracts, n=356

	PCA		K-Medians Cluster Analysis		Threshold Strategy	
Upscaled	**n=81**		**n=91**		**n=28**	
Change in…	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Improvement loans per capita	$241	$181	$120	$133	$153	$137
Median household income	-$3,908	$7,624	-$4,777	$8,942	-$409	$5,748
Median home value	-$116,988	$37,792	-$49,569	$46,574	-$92,650	$45,511
Mean dollar amount of home loans	$75,978	$58,640	$63,186	$52,218	$57,101	$56,531
Median gross rent	-$37	$273	-$29	$251	$111	$180
Proportion of middle- to high-income residents	0.8	7.2	-4.1	10.4	-3.3	6.5
Proportion of adults (aged 25+) with a college degree	2.0	4.6	1.6	4.6	4.5	3.5
Proportion of non-Hispanic White residents	-2.8	6.0	-3.8	5.9	0.8	3.3
Not Upscaled	**n=275**		**n=265**		**n=328**	

	PCA		K-Medians Cluster Analysis		Threshold Strategy	
Change in…	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Improvement loans per capita	$118	$136	$155	$163	$146	$158
Median household income	-$9,521	$9,714	-$9,434	$9,496	-$8,912	$9,533
Median home value	-$100,348	$51,424	-$122,872	$33,539	-$105,114	$49,345
Mean dollar amount of home loans	$34,199	$45,389	$37,015	$49,886	$42,561	$51,196
Median gross rent	-$49	$275	-$52	$282	-$60	$277
Proportion of middle- to high-income residents	-8.3	8.5	-7.0	8.5	-6.5	9.2
Proportion of adults (aged 25+) with a college degree	0.1	4.7	0.2	4.8	0.2	4.7
Proportion of non-Hispanic White residents	-3.7	6.4	-3.3	6.5	-3.8	6.4

As much as 12 percent of tracts were classified as gentrified using k-medians cluster analysis. Only approximately 4 percent of tracts were gentrified when we applied principal components analysis and the threshold strategy. The majority of census tracts in San Bernardino County were middle- to high-income and not upscaled.

Table 2.S29. Neighborhood Change Categories by Strategy, San Bernardino Census Tracts, n=356

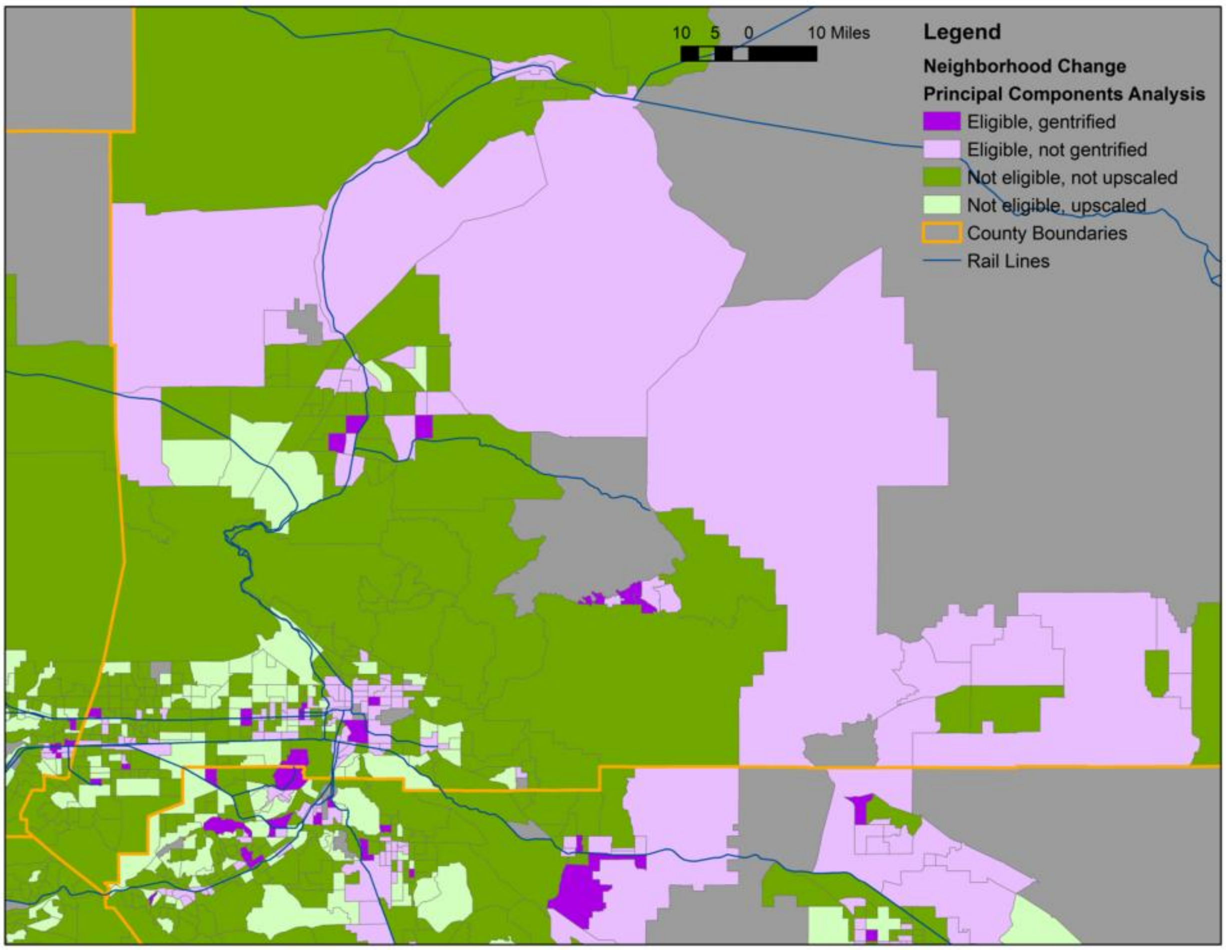
	PCA		K-Medians Cluster Analysis		Threshold Strategy	
	n	%	n	%	n	%
Low-income and gentrified	16	4.5	41	11.5	13	3.7
Low-income and not gentrified	92	25.8	67	18.8	95	26.7
Middle- to high-income and upscaled	65	18.3	50	14	15	4.2
Middle- to high-income and not upscaled	183	51.4	198	55.6	233	65.4

Associations between census tracts classified as gentrified across all three strategies were positive and small. Phi coefficients were approximately .2 for all comparisons.

Table 2.S30. Phi Coefficients of Gentrified vs. Not Gentrified Tracts across Strategies, San Bernardino County, n=356

	PCA	K-Medians Cluster Analysis	Threshold Strategy
PCA	1		
K-Medians Cluster Analysis	.18	1	
Threshold Strategy	.17	.21	1

Figure 2.S3. Map of Neighborhood Change, Census Tracts in San Bernardino County



Note: Eligible tracts had median household incomes that were <80% of the median household income for their respective counties.

Riverside County

Nearly 2.3 million people lived in Riverside in 2011-2015. Nearly half (47%) of its residents identified as Latina or Hispanic; 38 percent of residents were non-Hispanic White. Median household income for the county was $56,600. Among its census tracts, median household incomes ranged from $16,300 to $157,100. In 2006-2010, the average census tracts in Riverside County had 1,742. Mean vacancy rate was 12.6 percent.

From 2006-2010 to 2011-2015, median household incomes fell an average of $7,400 across Riverside County tracts. Median home values dropped an average of $105,900. On average, the fraction of non-Hispanic White residents in each tract decreased (3.3%), as did median gross rent (-$50). Over this period, the dollar amount of home improvement loans per resident did increase $208; average home loan amounts increased an average of $48,600.

Table 2.S31. Summary Statistics of Indicators Used to Measure Neighborhood Upscaling, Riverside County Census Tracts, n=441

	Mean	SD	Min	Max
Change in dollar amount of improvement loans per capita	$208	$209	-$108	$1,930
Change in median household income	-$7,395	$11,998	-$82,928	$37,002
Change in median home value	-$105,929	$58,758	-$563,536	$73,656
Change in mean dollar amount of loans originated for conventional home purchases	$48,620	$59,648	-$289,799	$324,142
Change in median gross rent	-$50	$277	-$1,396	$1,631
Change in proportion of middle- to high-income residents	-5.2	9.1	-53.5	19.7
Change in proportion of adults (aged 25+) with a college degree	0.1	5.4	-19.7	23.2
Change in proportion of non-Hispanic White residents	-3.3	6.9	-45.4	17.0

Sources: American Community Survey 2006-2010, 2011-2015 and Home Mortgage Disclosure Act Aggregate Tables 2010 and 2015

Principal components analysis, k-medians cluster analysis, and the threshold strategy identified 107, 80, and 40 upscaled census tracts, respectively. Upscaled tracts using PCA on average had increases in median household income and home loan amounts. Median household incomes across the 80 upscaled tracts using cluster analysis, on the other hand, decreased an average of $9,500, which was accompanied by an average 3.5 percentage point decrease in proportion of middle- to high-income residents in each tract. Average increases in home improvement and home purchase loan amounts were greatest among these 80 upscaled tracts compared to upscaled tracts identified through other strategies. Median gross rent on average decreased.

The threshold strategy identified the least number of upscaled census tracts in Riverside County. Median gross rents across these tracts climbed steeply, an average of $221. The proportions of residents with Bachelor's degrees on average increased (4.7%), as did real median household income. Across all three strategies, median home values in upscaled tracts dropped an average $100,000.

Table 2.S32. Summary Statistics of Indicators for Upscaled and Not Upscaled Neighborhoods by Strategy, Riverside County Census Tracts, n=441

	PCA		K-Medians Cluster Analysis		Threshold Strategy	
Upscaled	**n=107**		**n=80**		**n=40**	
Change in…	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Improvement loans per capita	$342	$258	$544	$225	$228	$284
Median household income	$433	$9,257	-$9,544	$13,102	$3,797	$7,074
Median home value	-$109,240	$47,995	-$111,047	$72,535	-$97,777	$74,342
Mean dollar amount of home loans	$73,305	$43,811	$75,831	$63,795	$35,402	$64,713
Median gross rent	$5	$336	-$50	$368	$221	$364
Proportion of middle- to high-income residents	1.8	6.4	-3.5	8.1	1.7	7.7
Proportion of adults (aged 25+) with a college degree	2.8	4.6	0.9	6.8	4.7	4.3
Proportion of non-Hispanic White residents	0.03	5.9	-2.2	7.7	0.8	3.2
Not Upscaled	**n=334**		**n=361**		**n=401**	
Change in…	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Improvement loans per capita	$165	$169	$134	$107	$206	$200
Median household income	-$9,902	$11,702	-$6,918	$11,706	-$8,511	$11,819
Median home value	-$105,034	$61,779	-$104,948	$55,238	-$106,880	$56,965

	PCA		K-Medians Cluster Analysis		Threshold Strategy	
Mean dollar amount of home loans	$40,712	$61,900	$42,590	$57,047	$49,938	$59,043
Median gross rent	-$71	$259	-$53	$259	-$80	$257
Proportion of middle- to high-income residents	-7.5	8.6	-5.6	9.2	-5.9	8.9
Proportion of adults (aged 25+) with a college degree	-0.7	5.3	-0.1	5.0	-0.3	5.3
Proportion of non-Hispanic White residents	-4.4	6.9	-3.6	6.7	-3.7	7.0

Nearly all of the 80 upscaled tracts identified through cluster analysis were middle- to high-income census tracts. Therefore, only 3 tracts were categorized as gentrified using this strategy. Four percent (n=19) of tracts were classified as gentrified using the threshold strategy, and 5 percent (n=24) were classified as gentrified using PCA.

Table 2.S33. Neighborhood Change Categories by Strategy, Riverside Census Tracts, n=441

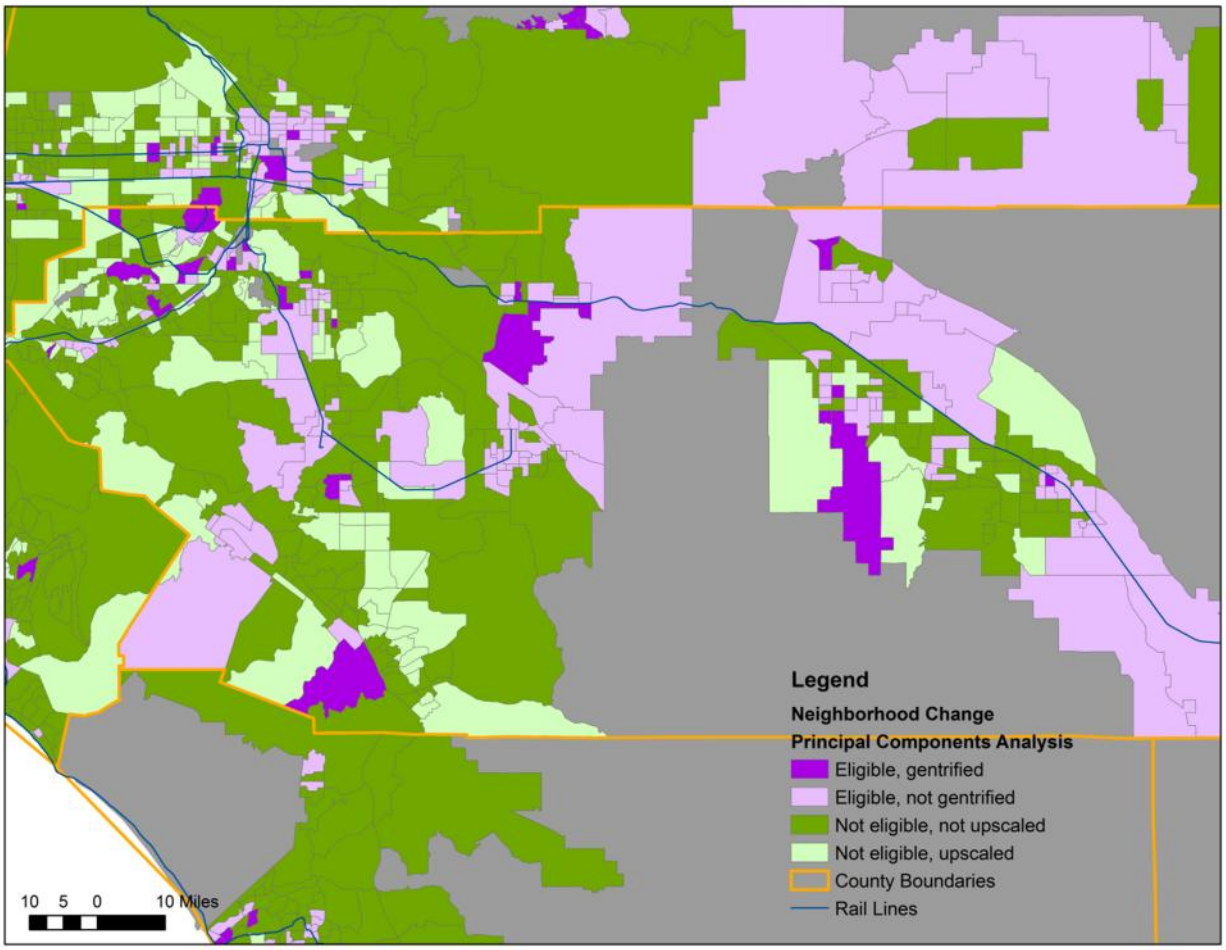
	PCA		K-Medians Cluster Analysis		Threshold Strategy	
	n	%	n	%	n	%
Low-income and gentrified	24	5.4	3	0.7	19	4.3
Low-income and not gentrified	118	26.8	139	31.5	123	27.9
Middle- to high-income and upscaled	83	18.8	77	17.5	21	4.8
Middle- to high-income and not upscaled	216	49	222	50.3	278	63

PCA results were positively associated with cluster analysis and threshold strategy results. The phi coefficients were approximately .3, indicating a low to moderate positive association. The association between gentrified tracts using cluster analysis and gentrified tracts using the threshold strategy was weaker (phi=.12).

Table 2.S34. Phi Coefficients of Gentrified vs. Not Gentrified Tracts across Strategies, Riverside County, n=441

	PCA	K-Medians Cluster Analysis	Threshold Strategy
PCA	1		
K-Medians Cluster Analysis	.35	1	
Threshold Strategy	.34	.12	1

Figure 2.S4. Map of Neighborhood Change, Census Tracts in Riverside County



Note: Eligible tracts had median household incomes that were <80% of the median household income for their respective counties.

San Diego County

San Diego County was home to nearly 3.2 million residents in 2011-2015. Non-Hispanic White residents (47%) represent the largest racial/ethnic group in this county, followed by Latina or Hispanic residents (33%). Eleven percent of San Diego County residents were Asian; 5 percent were Black or African American. Median household income was $64,300. At the census tract level, median household incomes ranged from $21,700 to $186,700. San Diego census tracts also had an average of 1,865 housing units in 2006-2010. The mean vacancy rate was 7.4 during that period.

Median home values in in San Diego County census tracts on average fell $92,000 during the study period. Median household incomes also decreased an average $4,100, and median rents increased. Home purchase and home improvement loan amounts increased during this period.

Table 2.S35. Summary Statistics of Indicators Used to Measure Neighborhood Upscaling, San Diego County Census Tracts, n=599

	Mean	SD	Min	Max
Change in dollar amount of improvement loans per capita	$220	$369	-$880	$3,747
Change in median household income	-$4,057	$11,425	-$80,775	$48,406
Change in median home value	-$92,000	$73,859	-$405,192	$322,329
Change in mean dollar amount of loans originated for conventional home purchases	$67,846	$85,991	-$314,044	$981,368
Change in median gross rent	$21	$274	-$961	$1,887
Change in proportion of middle- to high-income residents	-2.8	8.1	-26.7	20.4
Change in proportion of adults (aged 25+) with a college degree	1.7	5.6	-15.5	19.0
Change in proportion of non-Hispanic White residents	-2.5	6.6	-31.1	18.1

Sources: American Community Survey 2006-2010, 2011-2015 and Home Mortgage Disclosure Act Aggregate Tables 2010 and 2015

Both principal components analysis and cluster analysis identified 180 census tracts that experienced upscaling over the study period. Among both sets of upscaled tracts, the dollar amount of improvement loans per resident on average increased, as did median gross rent. The primary difference between the two sets was that for upscaled tracts using PCA, median household income on average increased $3,300. Median income for upscaled tracts using cluster analysis declined an average $3,700. Mean increase in the proportions of residents with Bachelor's degrees was also greater among census tracts in the former set (5.5% vs. 2.4%).

The threshold strategy identified 49 upscaled census tracts in San Diego County. Median gross rent increased an average $166 during the study period, the greatest average increase across all three strategies. Median household income also increased an average $6,700, as well as the proportion of residents with Bachelor's degrees in upscaled tracts (7.6%). Unlike upscaled tracts using other strategies, upscaled tracts identified through the threshold strategy on average had increases in the fraction of residents who identified as non-Hispanic White. Median home values on average fell in upscaled tracts across all strategies.

Table 2.S36. Summary Statistics of Indicators for Upscaled and Not Upscaled Neighborhoods by Strategy, San Diego County Census Tracts, n=599

	PCA		K-Medians Cluster Analysis		Threshold Strategy	
Upscaled	**n=180**		**n=180**		**n=49**	
Change in…	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Improvement loans per capita	$314	$405	$582	$476	$236	$271
Median household income	$3,294	$9,867	-$3,680	$13,606	$6,678	$9,146
Median home value	-$70,582	$69,591	-$89,242	$87,011	-$92,132	$81,799
Mean dollar amount of home loans	$107,657	$105,473	$93,216	$104,385	$94,240	$77,501
Median gross rent	$105	$335	$61	$330	$166	$206
Proportion of middle- to high-income residents	2.3	6.2	-2.6	7.0	3.2	7.1
Proportion of adults (aged 25+) with a college degree	5.5	5.2	2.4	5.7	7.6	4.6
Proportion of non-Hispanic White residents	-1.2	6.9	-3.0	7.1	3.2	4.6
Not Upscaled	**n=419**		**n=419**		**n=550**	
Change in…	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Improvement loans per capita	$180	$346	$65	$132	$219	$377
Median household income	-$7,216	$10,572	-$4,219	$10,362	-$5,014	$11,120
Median home value	-$101,919	$72,760	-$93,903	$66,447	-$92,535	$72,457

	PCA		K-Medians Cluster Analysis		Threshold Strategy	
Mean dollar amount of home loans	$50,744	$69,564	$56,947	$74,272	$65,495	$86,381
Median gross rent	-$14	$236	$5	$245	$9	$276
Proportion of middle- to high-income residents	-5.0	7.8	-2.9	8.5	-3.3	7.9
Proportion of adults (aged 25+) with a college degree	0.1	4.9	1.4	5.5	1.2	5.4
Proportion of non-Hispanic White residents	-3.1	6.5	-2.4	6.5	-3.0	6.6

The number of upscaled and low-income, in other words gentrified neighborhoods varied across the strategies. Employing principal components analysis, 9 percent (n=52) of San Diego County census tracts were categorized as gentrified. Approximately 4 percent of tracts gentrified under the threshold strategy, and although there were 180 upscaled census tracts using cluster analysis, only 11 gentrified.

Table 2.S37. Neighborhood Change Categories by Strategy, San Diego Census Tracts, n=599

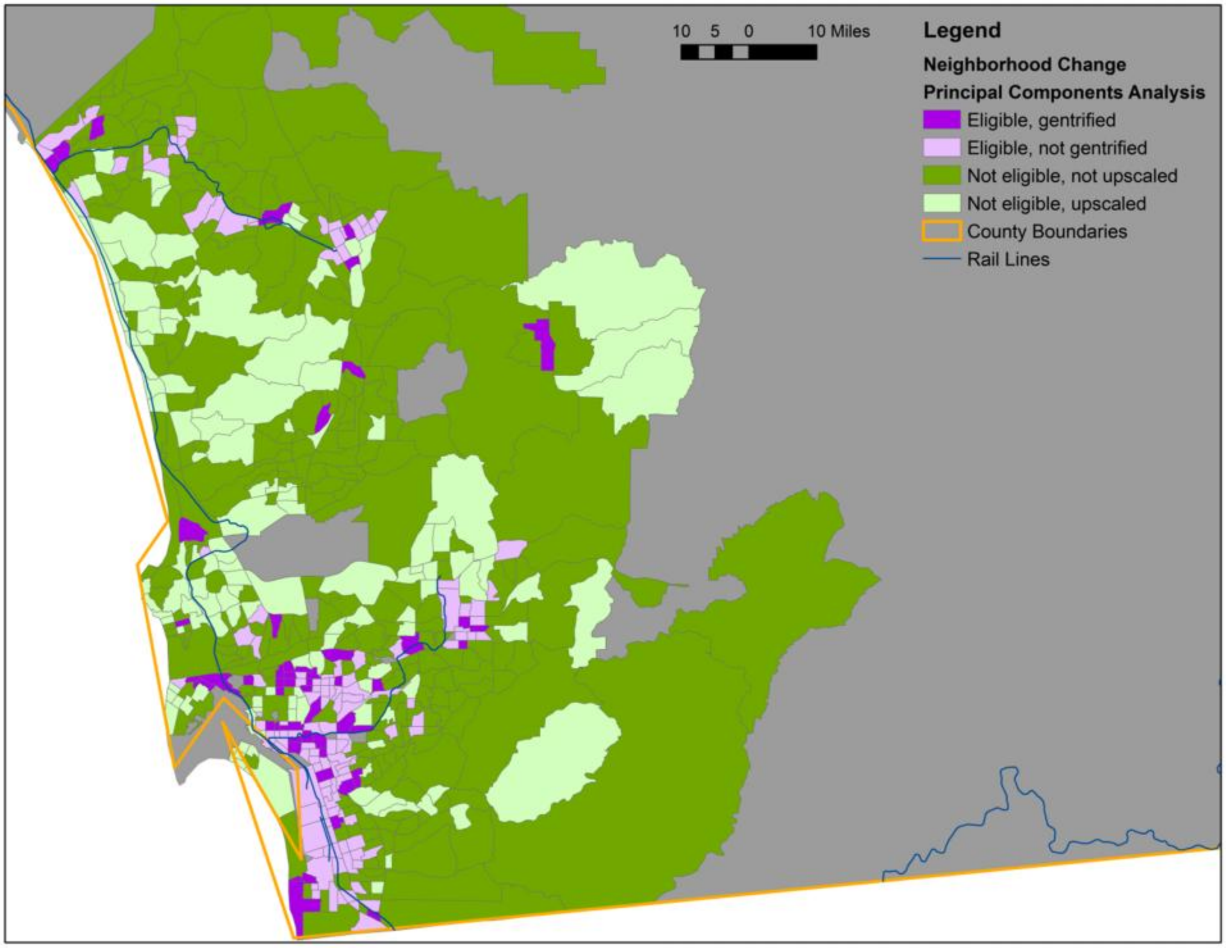
	PCA		K-Medians Cluster Analysis		Threshold Strategy	
	n	%	n	%	n	%
Low-income and gentrified	52	8.7	11	1.8	21	3.5
Low-income and not gentrified	126	21	167	27.9	157	26.2
Middle- to high-income and upscaled	128	21.4	169	28.2	28	4.7
Middle- to high-income and not upscaled	293	48.9	252	42.1	393	65.6

Gentrified tracts identified using PCA and gentrified tracts using the threshold strategy were most closely associated with a phi coefficient of .42. All other associations were very weak.

Table 2.S38. Phi Coefficients of Gentrified vs. Not Gentrified Tracts across Strategies, San Diego County, n=599

	PCA	K-Medians Cluster Analysis	Threshold Strategy
PCA	1		
K-Medians Cluster Analysis	.27	1	
Threshold Strategy	.42	.11	1

Figure 2.S5. Map of Neighborhood Change, Census Tracts in San Diego County



Note: Eligible tracts had median household incomes that were <80% of the median household income for their respective counties.

Ventura County

With an average 840,800 residents in 2011-2015, Ventura County is the least populous county in our study. Nearly half (47%) of its residents were non-Hispanic White, 42 percent identified as Latina or Hispanic, and 7 percent were Asian. Median household income in Ventura County was relatively high at $75,300. Median household incomes across census tracts in the county ranged between $32,400 and $204,400. In 2006-2010, the average census tract in Ventura County had 1,606 housing units. The mean vacancy rate was 5.6 percent.

Median home values fell an average $134,800 during the study period. Median household incomes in each census tract and proportions of residents with middle- to high-incomes also on average declined. Median rents, home improvement loan amount, and home purchase loan amounts increased. On average, the proportions of non-Hispanic White residents in each tract decreased 2.9 percentage points.

Table 2.S39. Summary Statistics of Indicators Used to Measure Neighborhood Upscaling, Ventura County Census Tracts, n=163

	Mean	SD	Min	Max
Change in dollar amount of improvement loans per capita	$133	$264	-$514	$2,130
Change in median household income	-$4,592	$14,061	-$38,037	$76,629
Change in median home value	-$134,759	$70,754	-$371,488	$293,258
Change in mean dollar amount of loans originated for conventional home purchases	$51,741	$95,294	-$623,349	$489,617
Change in median gross rent	$21	$326	-$873	$2,029
Change in proportion of middle- to high-income residents	-3.5	7.8	-26.1	17.5
Change in proportion of adults (aged 25+) with a college degree	1.0	4.9	-9.4	15.8
Change in proportion of non-Hispanic White residents	-2.9	6.8	-34.8	16.7

Sources: American Community Survey 2006-2010, 2011-2015 and Home Mortgage Disclosure Act Aggregate Tables 2010 and 2015

K-medians cluster analysis identified by far more upscaled census tracts than the other strategies. Over half (n=101) of tracts in Ventura County were classified as upscaled using this strategy.

On average, median gross rents across these 101 upscaled tracts increased $44, and the amount of home improvement loans per resident increased $135. Median household incomes on average decreased $3,100. In contrast, only 39 census tracts were categorized as upscaled using principal components analysis, 19 using the threshold strategy. Median household incomes on average increased among these upscaled tracts. Median household incomes on average increased $9,600 among the 19 tracts using the threshold strategy. Median gross rent also increased an average of $190, and mean increases in the proportions of non-Hispanic White residents and residents with Bachelor's degrees were greatest among these tracts compared to upscaled tracts using other strategies.

Among the 39 upscaled tracts using PCA, median gross rent increased an average $149, and home improvement loans increased $150 per resident. Median home values on average dropped $100,000 among upscaled tracts across all strategies.

Table 2.S40. Summary Statistics of Indicators for Upscaled and Not Upscaled Neighborhoods by Strategy, Ventura County Census Tracts, n=163

	PCA		K-Medians Cluster Analysis		Threshold Strategy	
Upscaled	**n=39**		**n=101**		**n=19**	
Change in…	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Improvement loans per capita	$150	$204	$135	$281	-$2	$145
Median household income	$6,090	$15,489	-$3,139	$14,938	$9,607	$18,419
Median home value	-$95,931	$64,736	-$115,316	$72,025	-$101,563	$82,914
Mean dollar amount of home loans	$26,697	$84,649	$11,102	$82,826	$68,672	$151,835
Median gross rent	$149	$374	$44	$364	$190	$213
Proportion of middle- to high-income residents	1.9	5.2	-3.3	7.9	-2.9	6.1
Proportion of adults (aged 25+) with a college degree	0.8	4.8	1.4	5.0	5.8	3.7
Proportion of non-Hispanic White residents	-2.0	7.0	-2.6	6.8	2.7	5.5
Not Upscaled	**n=124**		**n=62**		**n=146**	
Change in…	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Improvement loans per capita	$128	$281	$129	$235	$149	$271

	PCA		K-Medians Cluster Analysis		Threshold Strategy	
Median household income	-$7,952	$11,777	-$6,961	$12,250	-$6,246	$12,532
Median home value	-$146,971	$68,340	-$166,433	$56,080	-$138,624	$68,485
Mean dollar amount of home loans	$59,617	$97,391	$117,942	$75,375	$49,769	$86,972
Median gross rent	-$19	$300	-$17	$250	$1	$331
Proportion of middle- to high-income residents	-5.2	7.7	-3.7	7.7	-3.5	8.0
Proportion of adults (aged 25+) with a college degree	1.1	4.9	0.3	4.6	0.5	4.7
Proportion of non-Hispanic White residents	-3.2	6.8	-3.4	6.9	-3.6	6.7

Given the large number of upscaled tracts using cluster analysis, 34 (21%) of low-income census tracts were categorized as gentrified. Nine percent (n=15) of tracts of census tracts in Ventura County were classified as gentrified using PCA, and only 5 percent (n=8) of tracts were gentrified using the threshold strategy.

Table 2.S41. Neighborhood Change Categories by Strategy, Ventura Census Tracts, n=163

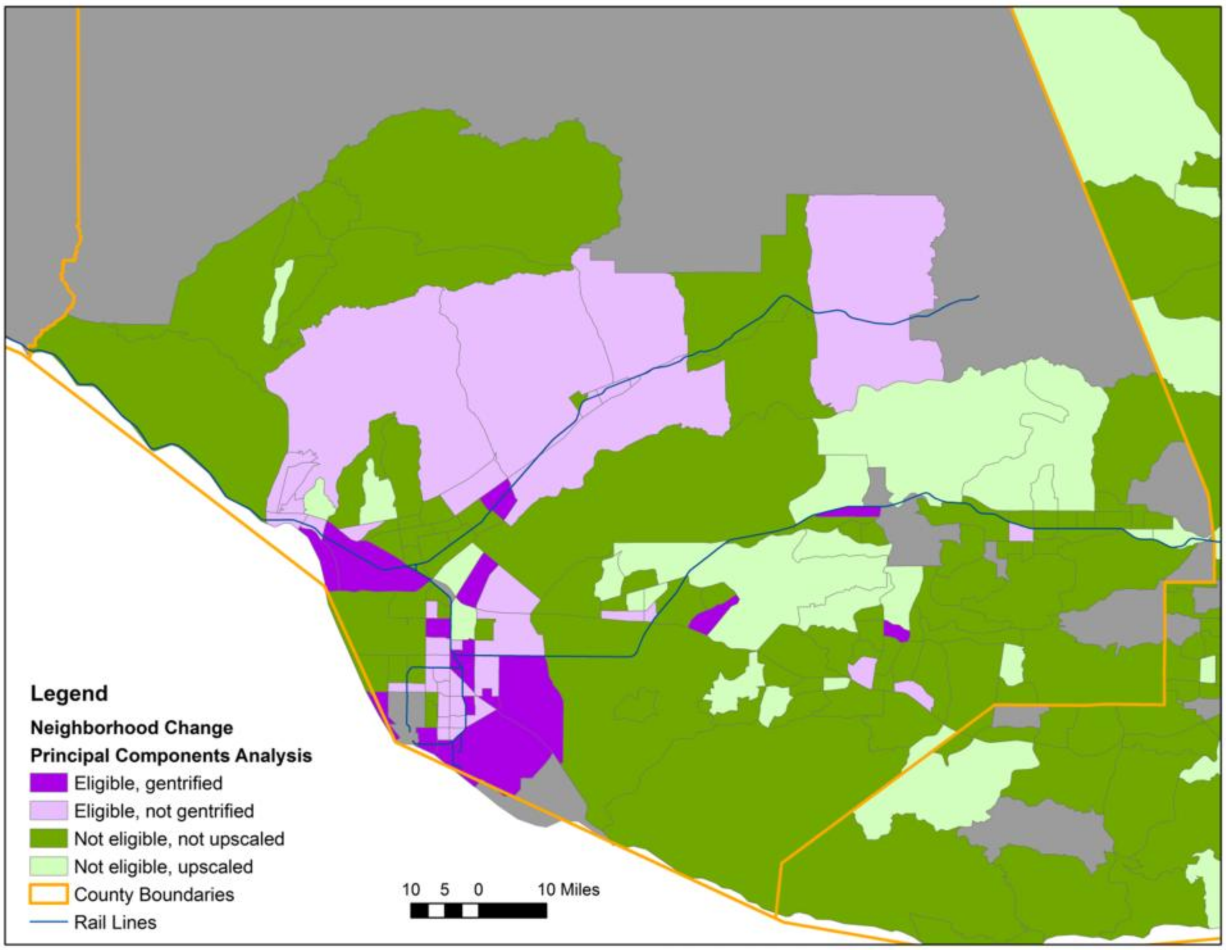
	PCA		K-Medians Cluster Analysis		Threshold Strategy	
	n	**%**	**n**	**%**	**n**	**%**
Low-income and gentrified	15	9.2	34	20.9	8	4.9
Low-income and not gentrified	38	23.3	19	11.7	45	27.6
Middle- to high-income and upscaled	24	14.7	67	41.1	9	5.5
Middle- to high-income and not upscaled	86	52.8	43	26.4	101	62

With the exception of one, all census tracts classified as gentrified using PCA were also classified as gentrified using cluster analysis. The phi coefficient was .57. All other comparisons indicated weak, positive associations between results.

Table 2.S42. Phi Coefficients of Gentrified vs. Not Gentrified Tracts across Strategies, Ventura County, n=163

	PCA	K-Medians Cluster Analysis	Threshold Strategy
PCA	1		
K-Medians Cluster Analysis	.57	1	
Threshold Strategy	.22	.23	1

Figure 2.S6. Map of Neighborhood Change, Census Tracts in Ventura County



Note: Eligible tracts had median household incomes that were <80% of the median household income for their respective counties.

Chapter 3: Impact of Gentrification on Adult Mental Health

Introduction

Gentrification is a process marked by accelerated physical restructuring, rapid economic growth, and notable shifts in the social and cultural characteristics of neighborhoods. At worst, gentrification can disrupt the social cohesion of a neighborhood, provoke feelings of cultural displacement, and sever social networks, thereby weakening individuals' protective factors for mental illness (Atkinson, 2002; Betancur, 2011; Lance Freeman, 2006; Newman & Wyly, 2006). At the same time, residents must contend with rising living costs and significant changes in their material circumstances. At best, residents of gentrifying neighborhoods also stand to benefit from improved housing quality, higher property values for home and commercial owners, better neighborhood amenities, richer retail and built environments, and potentially higher levels of collective efficacy (Lees et al., 2008; Steinmetz-Wood et al., 2017; S. Zukin et al., 2009). Although the benefits and harms of gentrification have been well documented, debate on whether gentrification is "bad" or "good" for residents and communities are ongoing, and the net impacts and distribution of the costs and benefits of this widespread phenomenon on adult well-being are not well understood.

Much has been written about neighborhoods and their influences on individual health outcomes (Diez Roux & Mair, 2010; Robert J. Sampson et al., 2002; Shankardass & Dunn, 2012). Risk for stress and mental health disorders such as depression have been linked to living in disadvantaged neighborhoods, residents' perceptions of social disorganization in their communities, the level of social cohesion, traffic stress, and other neighborhood features such as walkability (Berke, Gottlieb, Moudon, & Larson, 2007; Gary, Stark, & LaVeist, 2007; Gee & Takeuchi, 2004; Hill et al., 2005; Kim, 2010; Ross, 2000; Truong & Ma, 2006). Many of these studies assessed the effects of neighborhood characteristics, measured at a single time point, on mental health, but few studies have investigated the effects of neighborhood change on resident behaviors and outcomes. In the case of neighborhood decline, increasing poverty among moderate- to low-poverty neighborhoods were associated with more internalizing problems among boys (Leventhal & Brooks-Gunn, 2011). Proximity to and rise in foreclosures during the housing crisis, a period of rapid neighborhood change, have also been linked to declines in mental health (Downing, 2016; Houle, 2014). In the reverse scenario, declines in neighborhood disadvantage during childhood led to increases in residents' educational attainment and earnings (Johnston, 2017; Sharkey, 2012).

Studies exploring the relationship between gentrification and health are uncommon. Gentrification or the rapid neighborhood upscaling of historically under-resourced neighborhoods has been linked to greater risk for pre-term birth among non-Hispanic Blacks, but was associated with lower risk for pre-term birth among non-Hispanic Whites (Huynh & Maroko, 2014). In-depth interviews showed that high rents fueled by gentrification exacerbated food insecurity and hunger for people with low incomes and people living with HIV (Whittle et al., 2015). Using multi-level modeling, Gibbons and Barton (2016) observed some evidence that Black residents of gentrifying neighborhoods were 75% more likely to report poor or fair health relative to similar residents in other neighborhoods (Gibbons & Barton, 2016). Researchers also noted that gentrified neighborhoods with growing White versus Black resident populations had divergent effects on minority health. They concluded that gentrification harmed minority health. In a recent cohort study of New York City residents, Lim and colleagues observed that displaced residents of gentrifying neighborhoods had greater risks for emergency department visits, hospitalizations, and mental health-related visits than residents who remained (Lim et al., 2017). Residents were classified as displaced if they moved from gentrifying neighborhoods to poor, non-gentrifying neighborhoods. Among those who did not move, residents of gentrifying neighborhoods had higher rates of emergency department visits, lower rates of hospitalizations, and comparable rates of mental health-related compared to residents of non-gentrifying, poor neighborhoods.

The study by Lim and colleagues was one of the first to examine the impact of gentrification on adult mental health. Its chief strength was the use of administrative data, which allowed researchers to observe the healthcare utilization patterns of residents after leaving gentrifying neighborhoods. Administrative data are, however, limited by few demographic, socioeconomic, and social variables that often confound the relationship between neighborhood context and individual outcomes. Although authors used inverse probability of treatment weights to address systematic differences between displaced and not displaced groups, selection biases were not fully explored.

Using detailed respondent and residential information available in a large, continuous population-based survey in California, we sought to understand the causal effect of gentrification on adult residents' mental health and identify residents most impacted. We tracked neighborhood change from 2010 and 2015 and compared adults residents' likelihood of serious psychological distress based on neighborhood change category. Most recent studies on gentrification focus on periods between 2000 and 2010. Our study was set during a distinct time when the U.S. economy was starting to rebound from the Great Recession. We focused on neighborhoods in Southern California, a diverse region within which housing markets and prices rebounded more rapidly than many areas across the nation. We also recognized the challenges of identifying causal neighborhood effects and used multiple approaches to address nonrandom residential mobility and simultaneity.

Methods

Data Sources. Conducted by the UCLA Center for Health Policy Research, the California Health Interview Survey (CHIS) is the largest state health survey in the nation. Each year, more than 20,000 households in California participate in CHIS and share information about their physical health, mental health, environment, and behaviors. Cross-sectional data from five years of CHIS (2011, 2012, 2013, 2014, 2015) were pooled. The initial sample had 104,209 adult respondents aged 18 and over, 45,917 of whom lived in six select Southern California counties: Ventura, Los Angeles, Orange, San Bernardino, Riverside, and San Diego. Responses from interviewees who completed the survey by proxy were excluded. Respondents living in rural census tracts and tracts with fewer than 500 residents were also excluded. Data used to classify neighborhood change came from the 2006-2010 American Community Survey, 2011-2015 American Community Survey, and 2010 and 2015 Home Mortgage Disclosure Act (HMDA) aggregate reports. Census tract-level variables were then merged with CHIS responses using the census tract Federal Information Processing Standards (FIPS) codes of respondents' residences. 44,905 of 45,652 (98.4%) CHIS observations were successfully merged with neighborhood-level variables.

Instrumental and exclusion restriction variables were extracted from several external data sources: U.S. Census, American Community Survey, California Department of Education, National Center for Education Statistics (NCES) School Attendance Boundary Survey, and California Department of Transportation. These neighborhood-level variables were also merged with CHIS responses using census tract FIPS codes; 45,643 of 45,652 (90.0%) CHIS observations were successfully merged. The analytic dataset had 43,815 adult respondents with non-missing data.

Measures. Serious psychological distress (SPD) in the past year was the mental health outcome of interest. SPD was assessed using the Kessler 6 (K6), a 6-item assessment tool designed to estimate the prevalence of adults with non-specific psychological distress (Kessler et al., 2002). Respondents were asked to reflect on the worst month in the past year and indicate how often they felt nervous, hopeless, restless or fidgety, worthless, that everything was an effort, and so depressed that nothing can cheer them up. Respondents answered "All of the time," "most of the time," "some of the time," "a little of the time," or "none of the time." Responses were converted to scores and following recommended guidelines (Kessler et al., 2003), respondents with Kessler 6 scores of 13 and above (range 0 to 24) were categorized as having serious psychological distress in the past year.

The key independent variable was a neighborhood-level variable that categorized census tracts into four typologies: “Low-income and gentrified,” “Low-income and not gentrified,” “Middle- to high-income and upscaled,” or “Middle- to high-income and not upscaled.” These neighborhood change categories were developed based on eight indicators representing physical structuring, economic growth, and cultural shifts in neighborhoods from 2006-2010 to 2011-2015. See Chapter 2 for more details. We merged this variable to CHIS respondent addresses using the census tract FIPS codes corresponding to their residences.

Length of time at current address was used to measure residential stability, neighborhood attachment, and also served as an exposure measure (i.e., how long residents were exposed to neighborhood conditions and transitions). Long-term residents were classified as those who moved to their current neighborhood prior to 2010 (the start of the study period) and had lived in the neighborhood for at least 15 years. Residents who had lived in their neighborhoods for fewer than six years were categorized as recent residents. All other residents had lived at their current addresses for 6 to 14 years were categorized as average tenure residents.

Covariates measured socioeconomic position and other factors that predict both our key independent variable (neighborhood change category) and health. These covariates included demographic factors (age, gender, race/ethnicity, nativity, and English language proficiency), socioeconomic status (education, household income category, and homeownership), financial stressors (employment status and insurance status), social support (marital and parental status), health status (self-reported health, smoking status, and presence of chronic conditions), and neighborhood stressors (social capital and perception of neighborhood safety). See Table 3.S1 for a summary of variables included in outcome models.

Moderators & Subgroups. Long-term residents who lived in their current neighborhoods for at least 15 years likely had different responses to community change compared to residents who, perhaps attracted to the shifting characteristics of a neighborhood, recently moved to the community. We hypothesized that any effect of gentrification on mental health would be moderated by residents' attachment and therefore length of time in the neighborhood. As housing values and costs rise in gentrifying neighborhoods, we expected homeowners and renters to have disparate experiences related to financial security and housing burden and also explored homeownership as a moderating factor. Finally, renters with low incomes are at greatest risk of being pushed out of gentrifying neighborhoods. Low-income status (<200% federal poverty level vs. ≥ 200% federal poverty level) was also investigated as a potential moderator.

Figure 3.1 illustrates the hypothesized relationships between gentrification and adult mental health. Prior to upscaling (T1), households select the neighborhoods that best match their preferences and available resources. In the same pre-gentrification period, adults' mental health statuses can also influence their abilities to work, their socioeconomic positions, and residential location choices. As a result, living in a gentrified neighborhood may be endogenous. As gentrification shifts the physical, economic, and social characteristics of neighborhoods, households will move in and out of these neighborhoods (T2-T4). Residents who move in will likely differ from pre-existing residents who stay and residents who move out. During these periods, residents' mental health statuses may also impact their residential choices and mobility patterns. Finally, neighborhood changes caused by gentrification are expected to impact intermediary determinants of health—residents' living and material circumstances and psychosocial factors—(T3), which then shape their risks for serious psychological distress (T4). Because CHIS data is cross-sectional, we are unable to observe the mental health status of out-movers and the effect of moving out on mental health.

Residential Selection Variables. Decisions to move and choice of neighborhood depend on households' relative satisfaction with their current residential location, the cost of moving, individual and household characteristics, and neighborhood factors (Brown & Moore, 1970; Ritchey, 1976; Speare, 1974). Individual attributes such as life cycle, socioeconomic status, and social and kinship ties influence residential location decisions (Ritchey, 1976). We used respondent age, marital status, and parental status as proxies for life cycle status, included employment status, education, and household income variables as measures of socioeconomic status, and applied respondent homeownership status as a proxy for moving costs. Social capital and respondents' attachment to their neighborhoods were assessed using responses to questions about neighbors' willingness to help one another and whether neighbors can be trusted. Perception of safety was included as a predictor of residential selection because safety concerns contribute to stress and can push residents out of neighborhoods.

Individuals' preferences to live near people who are similar to them and reluctance to live in racially integrated neighborhoods (e.g., white avoidance) also influence residential location patterns (Charles, 2003; Jackelyn Hwang & Sampson, 2014; Ioannides & Zabel, 2008; Krysan, 2002; Krysan, Couper, Farley, & Forman, 2009; Quillian, 2002). The mobility of racially and ethnically marginalized were historically and are currently limited by structural barriers such as racially restrictive covenants and redlining (Charles, 2003; Glantz & Martinez, 2018). Real estate agents and rental property owners have and continue to inform and show homeseekers of color fewer available units than non-Hispanic White homeseekers (Turner, Ross, Galster, & Yinger, 2002; Turner et al., 2013). In turn, the neighborhood choice sets for racially and ethnically marginalized people are limited by socioeconomic status as well as individual and institutional prejudice and discrimination (Charles, 2003). To account for racially/ethnically motivated and restricted migration, we used respondent race/ethnicity, immigrant status, English proficiency, percent of non-Hispanic White residents, and census tract median household income, which was categorized into three categories (i.e., first quartile, second and third quartiles, and fourth quartile), as key residential selection variables. We also interacted the percent of non-Hispanic White residents variable with respondent race/ethnicity and interacted the median household income variable with respondent household income. Figure 3.2 summarizes the constructs and measures (residential and exclusion restriction variables) that predict residential location. Exclusion restriction variables were expected to predict residential location but not affect serious psychological distress.

Instrumental Variables. As noted in Figure 3.1, mental health status can influence residents' socioeconomic positions and can also determine who moves to and stays in gentrified neighborhoods. These relationships introduce endogeneity to our framework. To separate the potential impact mental health has on residents' likelihood of living in gentrified neighborhoods, we applied an instrumental variables estimation strategy. Although amenities such as public space and proximity to highways increase home values and attract investment to neighborhoods susceptible to gentrification (Chapple, 2009; Zuk et al., 2015), we searched for neighborhood characteristics that are associated with neighborhood change but that also did not influence mental health. For a discussion on past and current efforts to predict gentrification and displacement, see reports prepared by the Urban Displacement Project (Chapple et al., 2017). Candidate instrumental variables were hypothesized to predict the likelihood that respondents' neighborhoods gentrified between 2010 and 2015, but were expected to not (strongly) predict respondents' likelihoods for serious psychological distress. These instruments included: census tract's distance in miles to nearest rail station, distance in miles to nearest high-income neighborhood, difference in mean similar school rank and mean overall rank for all public elementary schools in a census tract, the interaction between whether respondents had children in the household and difference in school ranks, and the proportion of renters in a tract.

There is evidence that neighborhoods closer to rail transit stations or transit-oriented districts are more likely to gentrify; residential and commercial property values in these neighborhoods increase more rapidly compared to other neighborhoods (Armstrong & Rodríguez, 2006; Kahn, 2007; Zuk et al., 2015). We assumed that neighborhoods closer to rail stations were more likely to gentrify. The shapefile of rail stations in California as of 2013 came from the California Department of Transportation. Distance from the centroid of each census tract to the nearest rail station was calculated in meters using geographic information systems (GIS) software (ArcGIS 10.5.1) and then converted to miles.

Proximity to high-income neighborhoods was considered as a candidate instrument due to its negative relationship with gentrification (Austin Turner & Snow, 2001; Guerrieri, Hartley, & Hurst, 2013). It was unclear to us whether proximity to high-income neighborhoods was also strongly associated to individual mental health. We used GIS software to calculate each census tract's distance to the nearest high-income tract (defined as tracts with median household incomes greater than 1.32 times the county median) and converted the values to miles.

School quality influences neighborhood choice and home values (Kane, K. Riegg, & Staiger, 2006; Lerner, 2015; Zuk et al., 2015). Neighborhoods with high quality schools are more likely to attract households with higher incomes and education, and therefore, are more likely to gentrify. Using 2010 Academic Performance Index (API) data compiled by the California Department of Education and primary school attendance boundaries from the 2010-2011 and 2013-2014 National Center for Education Statistics (NCES) School Attendance Boundary Survey, we joined API data for public, non-charter elementary schools to school attendance boundaries and then spatially merged the boundaries to census tracts. Average scores and ranks were calculated if multiple attendance boundaries were located within a census tract. For school districts not represented in the NCES School Attendance Boundary Surveys, we assigned API scores and school ranks using boundary maps available on districts' websites. We then spatially joined public elementary schools and their API scores to the remaining census tracts with no API data. Average scores and ranks were calculated if multiple schools were located within a census tract. If a tract did not have a public elementary school located within its boundaries, we joined schools to tracts if schools were 1) within 1,500 feet of the tract and 2) belonged to the same school district that the tract was located within. Table 3.1 summarizes of the methods used to assign API data to census tracts. A total of 4,476 out of 4,549 (98.4%) of Southern California census tracts had API and school rank information.

We then subtracted mean statewide rank (API decile rank relative to all schools in the state) from mean similar school rank (decile ranks relative to schools with similar characteristics such as percent of teachers who are fully credentialed and percent of students who are English language learners). A positive difference score signaled that academic performance in these elementary schools was higher than their statewide rankings suggested, after taking into account school and student characteristics. We hypothesized that demand to reside in neighborhoods with positive difference scores was greater compared to neighborhoods with zero or negative scores, and that census tracts with positive scores were more likely to gentrify. We also assumed that school quality was more important to households that had children and explored the interaction between presence of children and difference scores as a as a candidate instrument for gentrification.

Finally, neighborhoods with greater shares of renter-occupied households are more likely to gentrify (Bates, 2013; Chapple, 2009; Kennedy & Leonard, 2001), and the contextual effect of homeownership rates on mental health may be small relative to individual characteristics. Percent of renter-occupied housing units in 2006-2010 was considered as a candidate instrument. See Table 3.2 for a summary of candidate instruments explored in this study.

Analyses. Descriptive analyses summarized outcomes and covariates by neighborhood change category (i.e., low-income and gentrified, low-income and not gentrified, middle- to high-income and upscaled, and middle- to high-income and not upscaled). Several models were employed to estimate the causal relationship between living in a gentrified neighborhood and likelihood of serious psychological distress. The first model was a probit model that assumed all explanatory variables were exogenous and that respondents' residential locations were randomly distributed. We used propensity score analyses, an endogenous treatment effects model, and matching by neighborhood characteristics to address nonrandom residential selection and unobserved heterogeneity between people in gentrified and not gentrified neighborhoods, and employed instrumental variables estimation to reduce bias arising from simultaneity.

<u>Probit Model.</u> A probit regression was performed to test the relationship between living in a gentrified neighborhood and the probability of having SPD in the past year. The reference group represented respondents who lived in low-income neighborhoods that did not experience gentrification. The model specification was as follows:

Probit Model for Serious Psychological Distress

$$y_i^* = \alpha_i + \theta_1 T_{1i} + \theta_2 T_{2i} + \theta_3 T_{3i} + X_i\beta + \varepsilon_i, \qquad \varepsilon \sim N(0,1)$$

$$y_i = \begin{Bmatrix} 1 \text{ if } y^* > 0 \\ 0 \text{ if } y^* < 0 \end{Bmatrix}$$

$$P(y_i=1) = \Phi(\alpha_i + \theta_1 T_{1i} + \theta_2 T_{2i} + \theta_3 T_{3i} + X_i\beta)$$

$$P(y_i=0) = 1-\Phi(\alpha_i + \theta_1 T_{1i} + \theta_2 T_{2i} + \theta_3 T_{3i} + X_i\beta)$$

, where T1 is an indicator for living in a low-income and gentrified neighborhood;

T2 is an indicator for living in a middle- to high-income and upscaled neighborhood;

T3 is an indicator for living in a middle- to high-income and not upscaled neighborhood;

Respondents living in low-income and not-gentrified neighborhoods represent the reference group;

X is a set of variables individual covariates associated with the outcome and year-fixed effects;

i = index for CHIS respondent.

Model misspecification, multicollinearity, calibration, and predictive accuracy were assessed using the Tukey and Pregibon link test, variance inflation factors, receiving-operating characteristic (ROC) curve, and Hosmer-Lemeshow goodness-of-fit test. Moderation of the impact of gentrification on mental health was examined through stratified analyses by neighborhood tenure, homeownership status, and low-income income status. Cluster-robust standard errors were estimated to adjust for intragroup correlation at the census tract level, and unless stated otherwise, all analyses were conducted using Stata 14.

The following analyses were limited to CHIS respondents who lived in neighborhoods considered low-income in 2006-2010.

Propensity Score Analyses and Endogenous Treatment Effects. Neighborhoods are constantly evolving, and residential mobility patterns are nonrandom. Threats to validity related to residential mobility include but are not limited to measures of exposure time, neighborhood change, selection bias, and endogeneity (Diez Roux, 2004; Galster, 2008; Hedman, 2011). We applied two approaches to address observed and unobserved differences between residents living in low-income neighborhoods that experienced gentrification and residents in low-income neighborhoods that did not. Propensity scores analyses were employed to balance respondents on characteristics that potentially influence both respondents' residential location and mental health (residential selection variables). Propensity scores represented the probability that residents lived in neighborhoods that gentrified between 2010 and 2015, conditional on individual characteristics such as life cycle and socioeconomic status, neighborhood qualities (e.g., percent residents who were non-Hispanic White and median household income), and interactions between individual and neighborhood-level variables (e.g., respondent race/ethnicity*percent non-Hispanic residents and respondent income category*median household income). The model specification for treatment assignment or living in a gentrified neighborhood was as follows:

Propensity for Living in a Gentrified Neighborhood

$$T_i^* = \tau + W_i\beta + X_i\beta + \eta_i, \quad \eta \sim N(0,1)$$

$$T_i = \begin{Bmatrix} 1 \text{ if } T^* > 0 \\ 0 \text{ if } T^* < 0 \end{Bmatrix}$$

$$P(T_i=1) = \Phi(\tau + W_i\beta + X_i\beta)$$

$$P(T_i=0) = 1-\Phi(\tau + W_i\beta + X_i\beta)$$

, where T is a dichotomous variable for living in a gentrified neighborhood;

W is a set of residential selection variables, including percent residents who were non-Hispanic White, median household income, respondent race/ethnicity*percent non-Hispanic residents, and respondent income category*median household income;

X is a set of individual covariates associated with the outcome and year-fixed effects;

i = index for CHIS respondent.

We matched each respondent in gentrified neighborhoods (T=1) with two respondents in not gentrified neighborhoods (T=0) with similar propensity scores and estimated the average treatment effect (ATE, the average difference between observed and potential outcomes for all respondents) and average treatment effect among the treated (ATT), among respondents who lived in gentrified neighborhoods. We also applied the inverse of propensity scores to compute weighted outcome averages for each treatment level (inverse-probability weighting), applied weighted outcome regression models for each treatment level (inverse-probability-weighted regression adjustment), and computed ATEs and ATTs for living in a gentrified neighborhood versus living in a low-income, not gentrified neighborhood. We assumed random treatment assignment among respondents with the same propensity scores, and assessed the overlap assumption, which requires that each respondent has a positive chance of being in either treatment level, by graphing the densities of propensity scores for respondents in gentrified and not gentrified neighborhoods.

Propensity score analyses helped reduce heterogeneity between respondents in gentrified and not gentrified neighborhoods by balancing treatment groups on individual and neighborhood characteristics observed in our dataset. However, unobserved factors such as proximity to friends and family might influence where respondents choose to live and impact their likelihoods for serious psychological distress. We employed an endogenous treatment effects model, which used the correlation between unobserved residential selection characteristics and unobserved characteristics that affect the outcome, to adjust the estimated effect of living in a gentrified neighborhood. Endogenous treatment effects models are formally estimated in two steps. The first equation models the likelihood of being in the treatment group, and the second equation models likelihood of having serious psychological distress in the past year. We used seemingly unrelated bivariate probit regression to estimate both probit models.

Endogenous Treatment Effects Model

First stage: Treatment model

$$T_i^* = \tau + W_i\beta + X_i\beta + \eta_i$$

$$T_i = \begin{Bmatrix} 1 \text{ if } T^* > 0 \\ 0 \text{ if } T^* < 0 \end{Bmatrix}$$

$$P(T_i{=}1) = \Phi(\tau + W_i\beta + X_i\beta)$$

$$P(T_i{=}0) = 1\text{-}\Phi(\tau + W_i\beta + X_i\beta)$$

Second stage: Outcome model

$$y_i^* = \alpha_i + \theta T_i + X_i\beta + \varepsilon_i$$

$$y_i = \begin{Bmatrix} 1 \; if \; y^* > 0 \\ 0 \; if \; y^* < 0 \end{Bmatrix}$$

$$P(y_i{=}1) = \Phi(\alpha_i + \theta T_i + X_i\beta)$$

$$P(y_i{=}0) = 1\text{-}\Phi(\alpha_i + \theta T_i + X_i\beta)$$

$$(\eta,\varepsilon)\text{~bivariate normal } [0,0,1,1,\rho]$$

, where T is an indicator for living in a gentrified neighborhood;

W is a set of residential selection variables, including percent residents who were non-Hispanic White, median household income, respondent race/ethnicity x percent non-Hispanic residents, and respondent income category x median household income;

X is a set of variables for individual covariates associated with the outcome and year-fixed effects;

i = index for CHIS respondent.

Matching by Neighborhood: Sharkey (2012) offered an alternative approach for addressing residential selection. He proposed matching respondents by neighborhood characteristics at the start of the study period *and* by neighborhood trends prior to that period. Doing so would allow us to compare respondents who had chosen very similar neighborhoods (Sharkey, 2012). Using coarsened exact matching (CEM), we matched CHIS respondents in gentrified neighborhoods to those in not gentrified neighborhoods by 1) the change in percent of non-Hispanic White residents in their neighborhoods from 2000 to 2010, 2) change in percent of residents in poverty from 2000 to 2010, 3) percent of non-Hispanic White residents in 2006-2010, and 4) percent of residents in poverty in 2006-2010. CEM temporarily bins each matching variable into meaningful groups, creates strata from the groups, sorts all observations into the strata, and discards all observations in a stratum that does not have at least one respondent who lived in a gentrified neighborhood and a respondent who lived in a not gentrified neighborhood (S. Iacus, King, Blackwell, & Porro, 2009; S. M. Iacus, King, & Porro, 2012). Scott's rule was applied to generate the bins, which minimized the integrated mean squared error (Scott, 1979). Note that unlike propensity score analyses, which matched or weighted respondents by their propensities to live in gentrified neighborhoods, CEM matched respondents "on neighborhoods that [respondents] have already selected" (Sharkey, 2012). Matching on neighborhood trends prior to 2010 also helped reduce selection bias stemming from respondents' different abilities to predict neighborhood change.

Treatment group effect. Using the CEM-matched sample and weights, we estimated the likelihood of having serious psychological distress in the past year, conditional on whether respondents lived in a gentrified neighborhood, individual covariates, and year-fixed effects. The estimate for θ is considered the "treatment group effect," the effect of living in a neighborhood on the verge of undergoing gentrification (Sharkey, 2012).

Treatment Group Effect Model (CEM-Matched Sample Only)

$$y_i^* = \alpha_i + \theta T_i + X_i\beta + \varepsilon_i, \quad \varepsilon \sim N(0,1)$$

$$(y_i) = \begin{Bmatrix} 1 \text{ if } y^* > 0 \\ 0 \text{ if } y^* < 0 \end{Bmatrix}$$

$$P(y_i=1) = \Phi(\alpha_i + \theta T_i + X_i\beta)$$

$$P(y_i=0) = 1-\Phi(\alpha_i + \theta T_i + X_i\beta)$$

, where T is an indicator for living in a gentrified neighborhood;

X is a set of variables for individual covariates associated with the outcome and year-fixed effects;

i = index for CHIS respondent.

Neighborhood change effect. Instrumental variables estimation was then used to address nonrandom out-migration of respondents during the gentrification period (Sharkey, 2012). The first stage model predicted the pace of neighborhood upscaling or gentrification respondents experienced, measured by principal component analysis scores for physical, economic, and social or cultural change between 2010 and 2015. For more details about this measure, see Chapter 2. Independent variables included an indicator for living in a gentrified neighborhood (T) and a set of individual covariates predicting mental health (X). The coefficient for T (π) measured the degree to which living in a gentrified neighborhood led to actual change in their neighborhoods (Sharkey, 2012). A large effect signaled that respondents living in gentrified neighborhoods experienced considerable neighborhood change.

The second stage model predicted the likelihood of having serious psychological distress on the predicted values of neighborhood upscaling (G*) and individual covariates. The estimate on G* (Δ) represented the change in likelihood of SPD associated with experiencing gentrification among residents who stayed in the neighborhood. Maximum-likelihood estimation was used to estimate both models.

Neighborhood Change Effect Model (CEM-Matched Sample Only)

First stage:

$$G = \tau + \pi T_i + X_i\beta + \eta_i$$

Second stage:

$$y_i^* = \alpha_i + \Delta G^*_i + X_i\beta + \varepsilon_i$$

$$y_i = \begin{Bmatrix} 1 \text{ } if \text{ } y^* > 0 \\ 0 \text{ } if \text{ } y^* < 0 \end{Bmatrix}$$

$$P(y_i=1) = \Phi(\alpha_i + \Delta G^*_i + X_i\beta)$$

$$P(y_i=0) = 1-\Phi(\alpha_i + \Delta G^*_i + X_i\beta)$$

, where T is an indicator for living in a gentrified neighborhood;

G is a score for neighborhood upscaling (gentrification);

G* is the predicted value of G;

X is a set of variables for individual covariates associated with the outcome and year-fixed effects;

i = index for CHIS respondent.

Instrumental Variables Estimation. In an effort to address endogeneity arising from mutual causality between living in a gentrified neighborhood and experiencing serious psychological distress, we implemented an instrumental variables strategy to estimate the causal effect of gentrification on respondents' likelihood of SPD. The first stage model predicted the likelihood that CHIS respondents' neighborhoods were gentrified using a set of exogenous instruments (Z) and individual covariates. Instruments were expected to predict gentrification and have no partial effect on SPD, controlling for other factors in the outcome model. In the second stage, SPD was regressed on the predicted probability that a respondent's neighborhood was gentrified, a set of variables associated with SPD, and year fixed-effects. We used two-stage least squares (2SLS) and seemingly unrelated bivariate probit regression to estimate both models.

Instrumental Variables Estimation - Bivariate Probit Regression

First stage: Treatment model

$$T_i^* = \tau + Z_i\beta + X_i\beta + \eta_i$$

$$T_i = \begin{Bmatrix} 1 \text{ if } T^* > 0 \\ 0 \text{ if } T^* < 0 \end{Bmatrix}$$

$$P(T_i=1) = \Phi(\tau + Z_i\beta + X_i\beta)$$

$$P(T_i=0) = 1-\Phi(\tau + W_i\beta + X_i\beta)$$

Second stage: Outcome model

$$y_i^* = \alpha_i + \theta T^P_i + X_i\beta + \varepsilon_i$$

$$y_i = \begin{Bmatrix} 1 \; if \; y^* > 0 \\ 0 \; if \; y^* < 0 \end{Bmatrix}$$

$$P(y_i=1) = \Phi(\alpha_i + \theta T^P_i + X_i\beta)$$

$$P(y_i=0) = 1-\Phi(\alpha_i + \theta T^P_i + X_i\beta)$$

, where T is an indicator that a respondent's neighborhood gentrified between 2010 and 2015;

Z is a set of candidate instruments for gentrification, including miles to nearest railroad line, miles to nearest high-income neighborhood, difference in mean similar school rank and mean overall rank for public elementary schools, the interaction between presence of children and difference scores, and the proportion of renters in a tract;

T^P is the predicted probability that a respondent's neighborhood gentrified;

X is a set of variables for individual covariates associated with the outcome and year-fixed effects;

i = index for CHIS respondent.

We also applied a two-stage residual inclusion approach. The first stage equation predicted the endogenous regressor, living in a gentrified neighborhood. Residuals from this estimation, the endogenous regressor, and individual covariates were then included as independent variables in the second stage to predict SPD.

Two-Stage Residual Inclusion

<u>First stage: Treatment model</u>

$$T_i^* = \tau + Z_i\beta + X_i\beta + \eta_i$$

$$T_i = \begin{Bmatrix} 1 \text{ if } T^* > 0 \\ 0 \text{ if } T^* < 0 \end{Bmatrix}$$

$$P(T_i=1) = \Phi(\tau + Z_i\beta + X_i\beta)$$

$$P(T_i=0) = 1-\Phi(\tau + W_i\beta + X_i\beta)$$

<u>Second stage: Outcome model</u>

$$y_i^* = \alpha_i + \theta T_i + \beta\eta^*_i + X_i\beta + \varepsilon_i$$

$$y_i = \begin{Bmatrix} 1 \text{ } if \text{ } y^* > 0 \\ 0 \text{ } if \text{ } y^* < 0 \end{Bmatrix}$$

$$P(y_i=1) = \Phi(\alpha_i + \theta T_i + \eta^*_i + X_i\beta)$$

$$P(y_i=0) = 1-\Phi(\alpha_i + \theta T_i + \eta^*_i + X_i\beta)$$

, where T is an indicator for living in a gentrified neighborhood;

Z is a set of candidate instruments for gentrification, including miles to nearest railroad line, miles to nearest high-income neighborhood, difference in mean similar school rank and mean overall rank for public elementary schools, the interaction between parent status and difference scores, and the proportion of renters in a tract;

η^* are residuals from the first stage equation;

X is a set of variables for individual covariates associated with the outcome and year-fixed effects;

i = index for CHIS respondent.

A summary of all methods and models explored are presented in Table 3.3.

Sensitivity Analyses. As described in Chapter 2, three strategies were used to develop a neighborhood change variable that categorized census tracts into low-income and gentrified, low-income and not gentrified, middle- to high-income and upscaled, or middle- to high-income and not upscaled neighborhoods. The three strategies included principal components analysis (PCA), K-medians cluster analysis, and a threshold strategy for identifying upscaled tracts. The PCA results represented the key independent variable in this study, and all analyses described above were repeated using results from the two other strategies. In addition, we replaced the key independent variable with the eight neighborhood change indicators originally used in Chapter 2, and repeated the probit regression and stratified analyses among respondents living in low-income neighborhoods. Indicators were standardized by county, so a change score of 1 in median home value represented a one standard deviation increase in median home value relative to other neighborhoods in the same county.

Results

Census tracts with median household incomes below 80% of their respective counties' median household incomes in 2006-2010 were categorized as low-income neighborhoods. Roughly a quarter (28%) of respondents in our sample lived in low-income neighborhoods. Approximately 7% (n=3,036) of respondents lived in low-income neighborhoods that underwent gentrification between 2010 and 2015; 21% (n=9,210) lived in low-income census tracts that did not. One-fifth (20%; n=8,849) of respondents lived in middle- to high-income neighborhoods that experienced upscaling, and half of respondents (52%; n=22,720) lived in middle- to high-income neighborhoods that did not experience upscaling. For brevity, neighborhood change categories were respectively referred to as "gentrified," "not gentrified," "upscaled," and "not upscaled" in the following discussion.

Seven percent of adults living in Southern California between 2011 and 2015 likely had serious psychological distress (SPD) in the past year. The fraction of respondents with serious psychological distress was greater among respondents living in low-income neighborhoods (9%); 6% of people living in middle- to high-income neighborhoods likely had SPD. See Table 3.4. A plurality of adults living in low-income communities (over 40%) were recent residents, people who moved to the neighborhood less than six years ago. Approximately 1 of 3 residents had lived in their communities for 15 or more years. A larger proportion of adults in gentrified neighborhoods were non-Hispanic White, and residents in not gentrified communities were more likely Latinx or Hispanic. Although homeownership and employment rates were similar in both communities, greater proportions of residents in gentrified neighborhoods had Bachelor's degrees and household incomes in the highest bracket compared to residents in not gentrified neighborhoods. Residents in gentrified neighborhoods were also less likely to report having fair or poor health, and a greater proportion felt safe in their neighborhoods all or most of the time compared to residents of not gentrified neighborhoods.

Residents of middle- to high-income neighborhoods had lived in their neighborhoods for longer periods than residents of low-income communities. Over 40% of respondents who resided in middle- to high-income neighborhoods were long-term residents. Compared to residents of low-income communities, adults in middle- to high-income were more likely non-Hispanic White, U.S. born, homeowners, insured, and married. Respondents living in middle- to high-income communities also had higher educations, higher incomes, and greater social capita scores; these respondents reported better health and were more likely to feel safe in their neighborhoods. Notably, residents of gentrified and upscaled neighborhoods were more likely non-Hispanic White, more educated, and wealthier than residents of not gentrified and not upscaled communities, respectively.

Probit Model. Table 3.5 presents the probit regression model results for all adults in our sample (n=43,815). Controlling for other factors in the model, on average, living in a gentrified neighborhood increased respondents' likelihood of serious psychological distress (b=.01; p=.02) relative to living in a low-income, not gentrified neighborhood (the reference category). This translated to an average 1 percentage point increase in SPD for living in a gentrified neighborhood (average marginal effect=1.1; p=.02). Living in a middle- to high-income neighborhood, upscaled or not, also increased respondents' likelihood of SPD relative to living in a not gentrified neighborhood. As expected, respondent age, gender, race/ethnicity, marital status, health, access to wealth, and social capita were significantly associated with SPD. The most influential predictors were having fair or poor health (b=.67), being aged 65 and over (b=-.51), and smoking (b=.38).

The pseudo R^2 for the model was .15; mean variance inflation factor was 1.5. Although Hosmer-Lemeshow goodness-of-fit (χ^2 (18) = 31.5; p=.03) was statistically significant, the model specification (link) test ($b(Xb)^2$)=-.01; p=.59) suggested that the probit model was not mis-specified. The model predicted our outcome with acceptable discrimination (area under the ROC curve=.79) and correctly classified 93% of observations with a probability threshold of .75. See graphs of sensitivity/specificity cutoffs and the ROC curve in Supplemental Materials.

Subgroup Analyses. Stratified probit regression results are presented in Table 3.6. For adults who recently moved to their neighborhoods, neighborhood change category did not have an effect on their likelihood of having serious psychological distress. Living in a gentrified (b=.23; p=<.01) or middle- to high-income and upscaled (b=.13; p=.04) neighborhood, relative to living in a not gentrified neighborhood, did increase likelihood of SPD for long-term residents. On average, living in gentrified neighborhoods, as opposed to living in low-income and not gentrified neighborhoods, increased likelihood of SPD by 2 percentage points (p<.01) for long-term residents.

Neighborhood change did not influence likelihood of SPD among respondents who owned their homes or had higher household incomes (200% FPL or greater). Renters and respondents with lower household incomes living in gentrified or upscaled neighborhoods had increased risks for serious psychological distress relative to similar adults living in low-income and not gentrified neighborhoods.

Propensity Score Analyses and Endogenous Treatment Effects. Our sample had 12,246 respondents who resided in low-income communities, a quarter (25%; n=3,086) of whom lived in communities that gentrified; 75% (n=9,347) lived in communities that did not. Candidate exclusion restriction variables for our propensity score analyses and endogenous treatment effects model included the proportion of non-Hispanic White residents in respondents' neighborhoods (census tracts), median household income, the interaction between the proportion of non-Hispanic White residents and respondents' races/ethnicities, and the interaction between median household income and respondents' income levels. Descriptive statistics for percent of non-Hispanic White residents and median household income are summarized in Table 3.7. We generated propensity scores, the conditional probability that a person lived in a gentrified neighborhood, for each respondent, and zero observations violated the overlap assumption. Overlapping propensity score density plots for people in gentrified communities and people in not gentrified communities also illustrated that each person in our sample had a positive probability for living in a gentrified neighborhood. See Figure 3.S3 in Supplemental Materials.

Adults who lived in gentrified neighborhoods were matched with two adults who lived in not gentrified neighborhoods using propensity score matching. Living in a gentrified neighborhood increased the probability that respondents had serious psychological distress by an average of 1.4 percentage points. This estimate was statistically significant (p=.04). See Table 3.8. Among respondents who resided in gentrified neighborhoods, living in gentrified versus not gentrified neighborhoods also increased their probabilities for SPD an average of 1.7 percentage points (ATT=.017; p=.01). Inverse-probability weighting and weighting with regression adjustment generated similar results. Living in a gentrified neighborhood increased the probability of SPD among all respondents in low-income communities

(ATE=.014) and among respondents who resided in gentrified communities. With the exception of the ATT using inverse-probability weighting, all estimates were statistically significant.

Conditional on variables associated with SPD, all exclusion restriction variables significantly predicted whether respondents lived in a gentrified community, and, with the exception of the percent non-Hispanic White variable, were not significantly associated with SPD. See Table 3.9. Seemingly unrelated bivariate probit regression estimated a rho (ρ) value of -.19. The Wald test of rho suggested that treatment and outcome models were not correlated ($\chi^2(1)=.787$; p=.38). Results also indicated that living in a gentrified community compared to a low-income community that did not gentrify increased likelihood of SPD (b=.408; p=.26). The average marginal effect was .067 (p=.34), a 6.7 percentage point increase in probability for SPD, but was not statistically significant.

Matching by Neighborhood. We used coarsened exact matching (CEM) to match respondents on four neighborhood characteristics: 1) percent of non-Hispanic White residents in 2006-2010, 2) percent of residents in poverty in 2006-2010, 3) change in percent of non-Hispanic White residents from 2000 to 2010, and 4) change in percent of residents in poverty from 2000 to 2010. Prior to matching, the overall L1 statistic, a measure of global imbalance across matching variables between adults in gentrified communities and adults in not gentrified neighborhoods, was .984. Each matching variable was coarsened into strata. Observations were placed across 582 strata, 110 of which had at least one respondent who resided in a gentrified neighborhood and at least one respondent who resided in a low-income neighborhood that did not gentrify. A total of 5,997 respondents were matched and retained, 5,976 (99.6%) of whom had non-missing data. The L1 of the matched sample was .985.

Table 3.10 summarizes the characteristics of respondents with non-missing data in the original and matched samples by neighborhood type. Although respondents in gentrified communities were generally similar to respondents in not gentrified neighborhoods in the original sample, the proportions of non-Hispanic White residents in both neighborhoods were equivalent after matching and weighting.

Respondents in gentrified and not gentrified communities were also more balanced across education and income measures after matching and weighting.

The estimated treatment group effect, the effect of living in a neighborhood on the verge of undergoing gentrification on past year SPD was .075. This coefficient translated to a 1.1 percentage point increase in the probability of SPD for living in a gentrified community as opposed to living in a low-income community that did not gentrify. The estimate was not statistically significant ($p=.26$). Results from the instrumental variables estimation are presented in Table 3.11. In the first stage, we included the indicator for living in a gentrified community as an instrument for predicting neighborhood upscaling. Living in a low-income neighborhood that underwent gentrification increased the neighborhood upscaling score an average of .87 standard deviations. This estimate was statistically significant ($p<.01$). The magnitude of this effect signals that adults who resided in gentrified neighborhoods experienced a considerable amount of change in their communities. The estimated neighborhood change effect was .09 and not statistically significant ($p=.27$), and the average marginal effect was .005 ($p=.664$). The Wald test of exogeneity produced a $\chi2(1)$ of .37 ($p=.54$), indicating that neighborhood change was exogenous.

<u>Instrumental Variables Estimation.</u> Descriptive statistics for four candidate instrumental variables are presented in Table 3.12. Please refer to Supplemental Materials for histograms of each variable. We tested whether each instrument had non-zero average causal effect on the gentrified status of respondents' neighborhoods. Controlling for individual covariates associated with SPD and survey year fixed-effects, only distance to nearest high-income neighborhood ($b=-.01$; $p<.01$) and difference in school rank score interacted with presence of children ($b=.06$; $p<.01$) significantly predicted whether respondents' neighborhoods were gentrified. Low-income neighborhoods that were farther from high-income tracts were less likely to gentrify from 2010 through 2015. In other words, low-income neighborhoods that were closer to high-income tracts were more likely to experience gentrification.

Difference in school rank scores was positively associated with gentrification among respondents with children. The effect was not significant among respondents who did not have children ($b<-.01$ $p=.88$). Both distance to nearest high-income neighborhood ($b<.001$; $p=.84$) and the interaction between difference school ranks and presence of children ($b=-.02$; $p=.41$) met the exclusion restriction assumption and were not conditionally associated with past year SPD.

We estimated likelihood of past year SPD using distance to nearest high-income neighborhood and the interaction between difference in school ranks and presence of children as instruments for gentrification, our endogenous key variable. Results from the two-stage least squares, two-stage residual inclusion, and seemingly unrelated bivariate probit regressions are presented in Table 3.13. Across all models, the instruments significantly predicted whether respondents' neighborhoods were gentrified in the first stage regressions. Two-stage least squares results indicated that living in a gentrified neighborhood on average decreased the likelihood of SPD by 4 percentage points. However, the estimate was not statistically significant ($p=.48$), and tests of endogeneity suggested that living in a gentrified neighborhood was exogenous (Durbin $p=.43$; Wu-Hausman $p=.43$). The association between living in a gentrified and SPD was positive in both two-stage residual inclusion and bivariate probit models but also not statistically significant. The estimate for rho was -.15. A Wald test indicated that rho was likely zero ($\chi^2(1)=.03$; $p=.87$).

Table 3.14 summarizes average marginal effects (AMEs) or average treatment effects (ATEs) of living in a gentrified neighborhood relative to living in a not gentrified neighborhood on past year serious psychological distress. Although not all statistically significant, AME or ATE estimates using ordinary least squares, probit regression, and propensity score analyses clustered around a 1 percentage point difference in the outcome between adults living in gentrified neighborhoods compared to those who lived in not gentrified neighborhoods. Endogenous treatment effects modeling and instrumental variables estimation generated AMEs that were larger in magnitude, but were not statistically significant. The estimated average marginal effect of gentrification using coarsened exact matching and instrument estimation was half a percentage point and also not statistically significant.

Sensitivity Analyses. Table 3.15 compares average treatment effects or average marginal effects for all models and approaches using three different measures of neighborhood change. The first column (Principal Components Analysis) presents information in Table 3.14. When analyses were repeated with neighborhood change categories identified using K-medians cluster analysis, living in a gentrified neighborhood, relative to living in a low-income and not gentrified neighborhood, was associated with the 1 percentage point reduction in prevalence of SPD. The average marginal effect was statistically significant (p=.049). Although average treatment effects associated with living in gentrified neighborhoods were also negative in propensity score analyses and endogenous treatment effects bivariate probit regression, the estimates were not statistically significant. Stratified analyses using the K-medians cluster analysis measure (not shown) indicate that the seemingly protective effect of living in a gentrified applied only to recent residents. The average marginal effect was -3.8 percentage points (p<.001).

With the exception of instrumental variables estimation results, all estimated effects for living in a gentrified neighborhood, using the threshold strategy measure of neighborhood change, were very small in magnitude, and all estimates were not statistically significant. Results (not shown) also did not vary across sub-groups (e.g., recent residents, renters, residents with low incomes, etc.).

Finally, we replaced the key independent variable with standardized neighborhood change indicators (continuous variables) that were used to develop the neighborhood change variable and repeated probit and stratified analyses for respondents who lived in low-income neighborhoods (n=12,246). Table 3.16 summarizes the results. Controlling for other factors in the model, living in a neighborhood where the proportion of residents with BA/BS degrees increased 1 standard deviation from 2006-2010 to 2011-2015 relative to other neighborhoods in the same county was associated with an average 0.7 percentage point increase in risk for SPD. Shifts in the educational backgrounds of residents had statistically significant effects on SPD for homeowners and residents with incomes above 200% the federal poverty level (FPL), but was not associated with SPD among recent or long-term residents, renters, and residents with low incomes. Among all respondents living in low-income communities, a 1 standard deviation increase in the fraction of non-Hispanic White residents was associated with decreased likelihood for SPD. Stratified analyses indicate that increases in the non-Hispanic White population reduced the risk for SPD of recent residents, homeowners, and residents with incomes above 200% FPL. Greater than average growth in median household income increased the likelihood of SPD for residents with incomes above 200% FPL, surges in median home values increased the likelihood of SPD for long-term residents, and gains in median rent that outpaced the county average increased risk for SPD for recent residents.

Discussion

As with any study that seeks to understand how neighborhoods potentially impact individual outcomes, there are methodological challenges to identifying the true effect of residing in a gentrified neighborhood on individuals' mental health. Neighborhoods are constantly changing, and people continuously moving in and out of them. Both processes are not random. Given that CHIS data is cross-sectional, we assessed residents' exposure to gentrification and employed a number of statistical adjustments to address selection bias arising from nonrandom migration (e.g., propensity score analyses, endogenous treatment effects, and matching by neighborhood and instrumental variables estimation). We tackled simultaneity between gentrification and the outcome with instrumental variables estimation. Our exclusion restriction variables, which included respondent's race/ethnicity, household income rank, race/ethnicity in relation to the racial composition of respondents' neighborhoods, and income relative to neighbors' incomes, conditionally predicted the likelihood that respondents lived in a gentrified neighborhood and met the exclusion restriction requirement. Future studies examining the effects of residing in gentrified neighborhoods on health outcomes or behaviors should consider these variables as candidate exclusion restriction variables.

Propensity score analyses results consistently estimated an average treatment effect or average marginal effect of 1 percentage point. The average marginal effect using the endogenous treatment effects model was 7 percentage points. The Wald test for rho was not statistically significant, indicating that conditional on the other covariates in the model, residing in a gentrified neighborhood was not endogenous. It may be that controlling for and balancing across observed residential selection variables adequately reduced bias from selective in-migration into gentrified neighborhoods.

Instrumental variables estimation results also suggested that mental health status did not strongly influence whether respondents lived in gentrified neighborhoods. Identifying satisfactory instruments for neighborhood characteristics have been elusive (Galster, 2008). Two of the four gentrification instruments we tested met the non-zero causal effect and exclusion restriction criteria. However, the R^2 in the first stage model was approximately .02, which indicates that most of the variance of gentrified neighborhoods across respondents was unexplained. We caution against concluding that the outcome is exogenous but are encouraged by the identification of two instruments. As additional instruments for gentrification are documented, instrumental variables estimation will likely emerge as a valuable and necessary tool for examining the health impacts on gentrification.

Patrick Sharkey's (2012) approach matches respondents, not by their propensity to live in gentrified communities, but by the similarity of the neighborhoods in which they reside. This unique approach reduces residential selection by matching respondents on their neighborhood decisions. Using coarsened exact matching, we achieved better balance in neighborhood characteristics for adults residing in low-income, gentrified and not gentrified communities. The average marginal effect for experiencing gentrification was .5 percentage points. The degree to which the estimated neighborhood change effect represented the causal effect of gentrification among adults who stayed in gentrifying neighborhoods depends on the matching variables and whether we achieved balance on neighborhood characteristics that are relevant to both our outcome and the likelihood that low-income neighborhoods experienced gentrification. We matched respondent neighborhoods on racial/ethnic composition, poverty rate, and changes in these neighborhood traits prior to the study period. It is possible that matching on other or additional neighborhood characteristics could have produced better balance, but as with most matching strategies, matching on more variables often results in loss of sample size and limits generalizability. Future research should test the relative effectiveness of the Sharkey approach to reduce selection bias.

We repeated all analyses with different measures of neighborhood change, the key independent variable. These measures categorized low-income and middle- to high-income neighborhoods as upscaled or not upscaled using three different strategies. As discussed in Chapter 2, overlap across strategies was low, so it was not unexpected that results in sensitivity analyses varied. We observed that living in a gentrified neighborhood was associated with *lower* risk for SPD relative to living in a not gentrified neighborhood, when using the neighborhood change variable created through cluster analysis. This relationship was only observed among recent residents or people who moved to gentrified neighborhoods in the past six years, and suggests that while gentrification increases stress for longtime residents, recent residents potentially benefit from the neighborhood changes. This relationship also likely reflects the selective processes of people moving to gentrified neighborhoods because of the changes and upscaling they observed in gentrified neighborhoods.

The measure of neighborhood change created using a threshold strategy identified neighborhoods as upscaled when neighborhoods experienced rapid increases in median rents and household incomes as well as greater than average increases in the fractions residents with higher education and residents who are non-Hispanic White. Employing this measure in our analyses, we found no difference in SPD risk between residents living in low-income and gentrified neighborhoods and similar residents living low-income and not gentrified neighborhoods. There are several potential explanations to consider. The first is that some criteria used to identify upscaled neighborhoods contribute to mental health stress while other neighborhood change indicators may be beneficial for mental health. The second consideration is that by focusing on four indicators of neighborhood change (the PCA measure joined eight indicators), the threshold strategy ignores other critical dimensions of gentrification and therefore does not adequately discriminate changing neighborhoods from gentrifying neighborhoods. The third consideration is that, on balance, gentrification does not have an impact on residents' mental health. Additional research on the effectiveness of the threshold strategy for identifying gentrified neighborhoods as well as the optimal set of criteria that should be used is warranted.

We also included the eight indicators of neighborhood change used to create the key independent variable directly into our outcome model and found that, after controlling for individual factors, an increase in the fraction of college educated residents increased risk for SPD of residents living in low-income neighborhoods. Interestingly, increases in the proportion of non-Hispanic White residents seemed to a serve as a protective factor and was associated with decreased risk for SPD. This relationship applied to recent residents, homeowners, and residents with incomes above 200% FPL, but did not have an effect on long-term residents, renters, and residents with low incomes. This finding demonstrates that different dimensions of neighborhood change may be beneficial for some residents, and other dimensions may be harmful for other groups. Results also offer some insight to the varying relationships observed between mental health stress and the different measures of neighborhood change. If an approach for identifying upscaled neighborhoods prioritizes racial transition over change in the social class of residents, the relationship between living in a gentrified neighborhood and mental health stress would likely be negative. Moreover, results also raise questions about the racial/ethnic identities of in-movers versus pre-existing residents, racial/ethnic concentration in gentrifying neighborhoods, and how these factors influence the relationship between gentrification and mental health. Taking all observations into account, sensitivity analyses results do not contradict our main findings but highlight the importance of the strategy used to identify gentrification and understand its impact on health and well-being. Results also suggest that gentrification likely affects residents' mental health through a constellation of pathways that is dependent on their socioeconomic position, racial/ethnic identity, and relationships with their neighborhoods.

Neighborhood selection is "more than a statistical nuisance" and can severely mask true neighborhood effects, if any (Sampson & Sharkey, 2008). Across nearly all models and statistical adjustments used to control for selection bias, we observed a positive conditional relationship between living in a gentrified neighborhood and serious psychological distress. Half of the estimates were statistically significant at the .05 threshold. On balance, we believe gentrification negatively impacts the mental health of renters, low-income residents, and long-term residents, if reverse causality is nonexistent or negligible. This suggests that despite intensified investment in neighborhoods that might bring more amenities and resources to residents, the average effect of gentrification on these residents' mental health was negative. Although a 1 percentage point difference appears to be small, this average marginal effect is roughly equivalent to a 13% increase in SPD among adult Southern California residents. Individuals with SPD likely had a DSM-IV disorder other than substance use disorder in the year prior to completing the CHIS survey (Kessler et al., 2003).

Insights on the pathways through which living in gentrified neighborhoods contributes to poorer mental health can be gleaned from stratified analysis results. Gentrified neighborhoods negatively impacted select groups of residents and not others. Among recent residents, people who had lived in their neighborhoods for fewer than six years, living in a gentrified neighborhood did not negatively impact their risks for serious psychological distress (and might have improved their mental health).

Several reasons might explain the null effect. The first is insufficient exposure to rapid neighborhood change. Recent residents might have not yet developed attachments to their new communities and were therefore less susceptible to stressors associated with neighborhood change. Selective in-migration to gentrified neighborhoods is another factor to consider. Gentrifying neighborhoods offer more affordable housing options compared to middle- and high-income neighborhoods. And as private and public investments help transform these neighborhoods, gentrifying neighborhoods become more attractive places to live to many prospective residents. Recent residents of gentrified neighborhoods might have perceived neighborhood change as a positive process and moved to the neighborhoods for this reason.

In contrast, residents who had lived in their communities for 15 or more years and experienced gentrification had greater risk for SPD in the past year compared to similar long-term residents of neighborhoods that did not gentrify. Longtime residents have reported loss of community and feeling that they didn't belong as a result of gentrification (Burns et al., 2012; Lance Freeman, 2006; Lees et al., 2008). Long-term residents are also more likely to experience cultural displacement or the replacement of their norms and values (Davidson & Lees, 2010; Lance Freeman, 2006; D. Hyra, 2015; Sharon Zukin, 2009). Similarly, residents can experience "symbolic displacement" or feelings of isolation and dislocation as the neighborhood around them transforms (Atkinson, 2015). For longtime residents of gentrified neighborhoods, the distress associated with feeling left behind, pushed out, and/or replaced might have outweighed positive changes in the neighborhood and increased their risk for mental distress.

Residing in a gentrified neighborhood also negatively impacted the mental health of adults with low-incomes and renters but did not affect homeowners and people with higher incomes. These results suggest that gentrification influences mental health through heightened financial pressures associated with higher living costs. Home values and rents appreciate rapidly in gentrifying neighborhoods, and renters in non-rent-controlled housing units are particularly impacted. Although homeowners also contend with rising housing costs, any negative impacts on their material circumstances may be offset by considerable home equity gains. In addition to greater financial stressors, low-income and long-term residents may feel excluded from and alienated by the changes in their neighborhoods. Investments in gentrifying neighborhoods offer residents expanded food and retail options. However, new retail in gentrifying neighborhoods often cater to recent residents with higher education and incomes and may be inaccessible to residents with low incomes (Deener, 2007; Monroe Sullivan, 2014; S. Zukin et al., 2009). Finally, as gentrified neighborhoods become less affordable and "friendly" to longtime residents, renters and low-income residents must contend with fears of displacement, which contribute to stress (Atkinson, 2002; Newman & Wyly, 2006).

It should be noted that for long-term residents, low-income adults, and renters, living in a middle- to high-income neighborhood that experienced upscaling (i.e., rapid economic growth and physical and cultural changes) also increased their risks for serious psychological distress. Despite living in more-resourced communities, rapid neighborhood change negatively impacted mental health for these residents. We also observed that the effects of gentrification or upscaling on serious psychological distress were greatest among long-term residents. As mentioned earlier, these residents are at greater risk of experiencing loss of connectivity and cultural displacement as their communities gentrified, and although not all long-term residents have low incomes, any cumulative increases in household income were likely outpaced by rising costs in their neighborhoods. Finally, after living in the neighborhood for 15 or more years, fear of displacement likely carried a heavy toll on longtime residents' mental health.

Limitations. This study focused on the mental health effects of gentrification on the current residents of gentrified neighborhoods. Not represented in our study are former residents who moved away. Based on our findings, we posit that former residents, particularly renters and people with low incomes, contending with unsustainable and rapidly increasing living costs, had limited options but to leave their communities. In doing so, these displaced residents would likely experience "root shock," disruption in their social networks, unexpected moving expenses, and other stressors that negatively impacted their mental health (Fullilove, 2009). In addition, vulnerable residents who moved out of gentrifying neighborhoods had greater risk of downward mobility and moving to "economically worse-off neighborhood(s)" (Ding et al., 2016). It's less clear whether homeowners who move out of gentrifying neighborhoods fare better or worse than homeowners who move out of non-gentrifying neighborhoods. On average, homeowners in gentrifying neighborhoods benefit from relatively greater increases in home values and may potentially experience upward economic mobility from selling their homes. It's unknown whether the pressures of moving and leaving one's community overshadowed the economic benefits gained from owning a home in gentrified neighborhoods.

Data used in this study was cross-sectional, and respondents in our analytic dataset included in-movers and stayers with distinct motivations, socioeconomic profiles, and experiences. We separated in-movers from pre-existing residents in stratified analyses, but without panel data, were unable to adjust for selective out-migration and observe displacement from gentrified neighborhoods. We did find evidence that current residents of gentrified communities experienced a substantial amount of community change and that gentrification increased risk of serious psychological distress for current residents, the "compliers" in an experimental setting (Angrist, Imbens, & Rubin, 1996). Using a variety of statistical adjustments and the rich data offered in the California Health Interview Survey, we were able to minimize residential selection bias and unobserved heterogeneity to estimate the causal effect of gentrification on residents' mental health, which was this study's greatest strength. Although not definitive, our study offers evidence that living and staying in gentrified neighborhoods has a mental health cost on adults with low income, renters, and long-term residents. If a majority of households who moved out of gentrified neighborhoods were priced or forced out, the full effect of gentrification is likely greater than presented in this study.

Figures and Tables

Figure 3.1. Conceptual Framework Linking Gentrification to Serious Psychological Distress for Current Residents (In-Movers & Stayers)

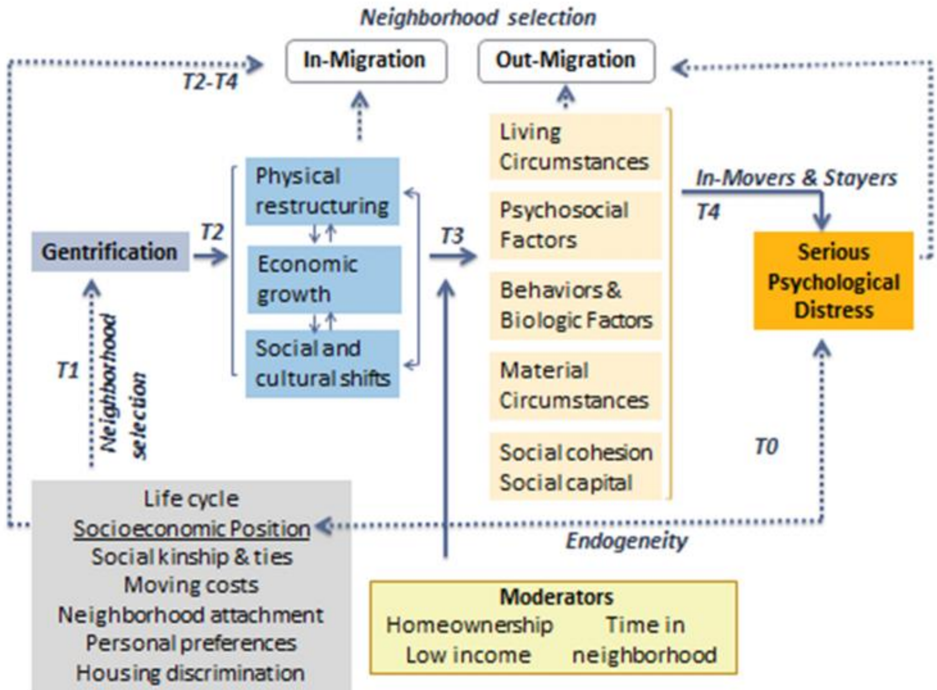


Figure 3.2. Residential Selection, Exclusion Restriction, and Instrumental Variables Related to Neighborhood Location and Gentrification

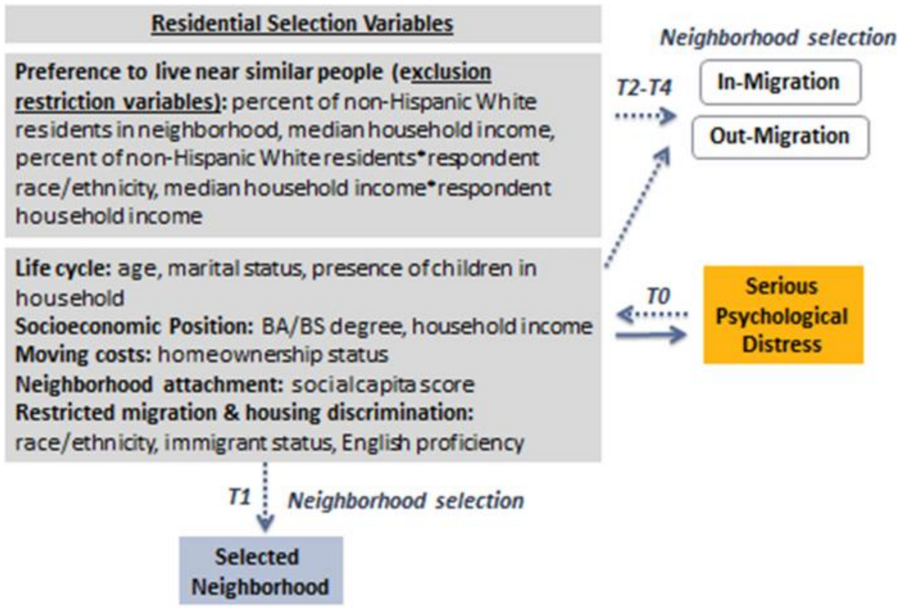


Table 3.1. Methods Used to Assign School Academic Performance Index (API) Data to Census Tracts

	Frequency	Percent
1. Merge schools to attendance boundaries to tracts	2,057	46.0
2. Visual assignment using attendance boundary maps	38	0.9
3. Average data across schools located inside tracts	1,172	26.2
4. Merge data for nearest schools within the same unified school district to tracts	950	21.2
5. Merge data for nearest schools within the same elementary school district to tracts	259	5.8
Total	**4,476**	**100**

Table 3.2: Candidate Instruments for Gentrification

Candidate Instruments	Rationale
Census tract distance from nearest rail station	Neighborhoods closer to rail stations are more likely to gentrify. It is also cheaper to convert existing rail stations and lines to rail transit lines than to build new infrastructure (cost shift).
Adjusted school quality relative to overall quality among respondents with children	Neighborhoods with quality schools are more likely attract gentrifiers. School quality can also reflect community investments that affect health.
Proximity to high-income neighborhood	Low-income neighborhoods that are in close proximity to high-income neighborhoods are more likely to gentrify. It’s unclear whether living near a high-income neighborhood affects health.
Proportion of renters	Neighborhoods with higher shares of renter-occupied are more likely to gentrify. The contextual effect of neighborhood ownership rate may be small relative to individual characteristics (e.g., SES, ownership, etc.).

Table 3.3. Statistical Method(s) or Adjustments Applied to Address Methodological Challenges Related to Mobility

Threats to Validity	Expected Impact on Results, Direction of Bias	Statistical Method(s) or Adjustments Applied
Exposure time - *Mobility in and out of neighborhoods can lead to inadequate exposure to the impacts of gentrification.*	If gentrification has a negative impact on residents and a large proportion of residents have inadequate exposure to its impacts, the estimate on gentrification would be positively biased toward zero.	Tenure in neighborhood was included as a covariate. Analyses were also stratified by tenure (recent vs. long-term residents). We hypothesized that residents who lived in their neighborhoods before and through the period of neighborhood experienced cumulative effects of gentrification.
Neighborhood change - *Neighborhood conditions may change over time, therefore changing residents' behaviors and outcomes.*	The regressor of interest is a measure of neighborhood change for low-income and middle- to high-income neighborhoods. Validity of estimates for this variable is dependent on model specification and ability to address selection bias and endogeneity.	Not applicable.
Selection bias - *Decisions to move to or stay in gentrifying neighborhoods are not random. Factors that influence residency in gentrified neighborhoods can also impact outcomes.*	If gentrification has a negative impact on residents and adults who move to or remain in gentrified neighborhoods disproportionately have traits or resources that promote health, the estimate on gentrification would be positively biased toward zero.	Propensity score analyses to balance adults living gentrified and not-gentrified neighborhoods on observed characteristics related to both residential selection and outcomes. Treatment effects (bivariate probit) model to control for selection bias arising from the endogenous choice of living in gentrified neighborhoods and unobserved differences between residents in gentrified and not-gentrified neighborhoods. Match CHIS respondents by neighborhood characteristics and neighborhood trends prior to gentrification using coarsened exact matching, followed by instrumental variables estimation, to address nonrandom selection into and out of gentrified neighborhoods.
Endogeneity - *Mutual causality between living in gentrified*	If gentrification has a negative impact on residents and people with higher socioeconomic	Instrumental variables estimation (two-stage least squares, bivariate probit, and two-stage residual

Threats to Validity	Expected Impact on Results, Direction of Bias	Statistical Method(s) or Adjustments Applied
neighborhoods and the outcome and/or individual characteristics that affect the outcome.	status are more likely to move to gentrified neighborhoods and living in these neighborhoods increase their material circumstances, the estimate on gentrification would be positively biased toward zero.	inclusion models) to identify the effect of gentrification on outcomes independent of other factors. The first stage model estimates the probability that respondent's neighborhood was gentrified.

Table 3.4. Characteristics of Adults Aged 18 and Over Living in Southern California Counties by Neighborhood Type[a], n=43,815

	Low-income & gentrified	Low-income & not gentrified	Middle- to high-income & upscaled	Middle- to high-income & not upscaled
	n=3,036	n=9,210	n=8,849	n=22,720
Outcome: Likely had serious psychological distress in the past year	9.1	9.0	5.7	6.0
Tenure in neighborhood				
1-5 years (recent resident)	43.2	46.3	32.0	32.9
6-14 years	25.8	24.9	23.7	24.6
15+ years (long-term resident)	31.0	28.8	44.3	42.5
Gender				
Female	59.5	59.9	58.4	57.8
Male	40.5	40.1	41.6	42.2
Age Category				
18-25	9.7	11.1	6.3	7.6
26-45	23.8	25.2	19.2	19.3
46-64	31.5	33.6	36.7	36.9
65+	35.0	30.2	37.7	36.2
Nativity				
Born outside U.S.	41.1	42.8	23.7	25.9
Born in U.S.	58.9	57.2	76.3	74.1
English Proficiency				
Speaks only English or speaks English well	75.4	72.3	93.1	90.4
Speaks English not well or not at all	24.6	27.7	6.9	9.6
Race/Ethnicity				
Latinx/Hispanic	38.9	45	16.6	21.4
Non-Hispanic White	36.5	31.7	65	59.4
Black	9.6	10.1	5.1	5.5
Asian, AIAN, NHPI, Two or More Race	14.9	13.1	13.4	13.8
Has Bachelor's degree or higher	29.5	21.8	51.9	43.6
Household Income				
1st quartile	39.1	44.7	14.8	18.7
2nd and 3rd quartile	48.0	45.7	50.7	52.4
4th quartile	12.9	9.6	34.6	28.9
Homeownership Status				
Rent or other arrangement	59.5	60.4	29.6	30.7

	Low-income & gentrified	Low-income & not gentrified	Middle- to high-income & upscaled	Middle- to high-income & not upscaled
Own home	40.5	39.6	70.4	69.3
Employment Status				
Employed or not looking	93.1	92.1	95.9	94.9
Unemployed	6.9	7.9	4.1	5.1
Insurance Status				
Currently uninsured or uninsured any time	20.0	23.0	10.5	12.6
Insured all year	80.0	77.0	89.5	87.4
Marital Status				
Married/living with partner	42.0	45.5	55.5	54.8
Widowed/separated/divorced	32.4	30.0	27.2	27.3
Never married	25.6	24.5	17.3	17.9
Reported fair or poor health	29.0	33.8	16.1	19.5
Chronic Conditions				
No reported conditions	67.8	67.7	71.0	69.5
Asthma, diabetes, &/or heart disease	32.2	32.3	29.0	30.5
Current smoker	12.2	13.4	9.0	9.7
Social Capital Score				
2	1.2	2.1	0.5	0.7
3	2.7	2.6	0.9	1.1
4	12.1	13.7	4.6	5.7
5	16.5	18.5	9.9	10.9
6	46.6	45.1	52.3	51.8
7	12.4	10.7	15.4	14.7
8	8.5	7.4	16.3	15.2
Feels safe in the neighborhood all or most of the time	82.4	78.2	94.6	93
Children in household	21.1	26.2	20.8	21.7

Sources: California Health Interview Survey 2011, 2012, 2013, 2014, 2015; American Community Survey 2006-2010 and 2011-2015; Home Mortgage Disclosure Act Aggregate Data 2010 and 2015

[a] All differences ($\chi 2$) between respondents in low-income versus middle- to high-income neighborhoods were statistically significant ($p<.05$).

Table 3.5. Probit Regression Model Results[a] for Past Year Serious Psychological Distress, Adults Aged 18 and Over Living in Southern California Counties, n=43,815

	Coefficient	Standard Error[b]	p-value
Neighborhood Type - ref: Low-income and not gentrified			
Low-income and gentrified	.095	.041	.02
Middle- to high-income and upscaled	.085	.032	.01
Middle- to high-income and not upscaled	.059	.027	.03
Tenure in neighborhood - ref: 6-14 years			
1-5 years (recent resident)	.072	.027	.01
15+ years (long-term resident)	-.049	.029	.09
Gender - ref: Female			
Male	-.206	.022	<.01
Age Category - ref: 46-64			
18-25	.198	.041	<.01
26-45	.143	.031	<.01
65+	-.506	.030	<.01
Nativity - ref: Born outside US			
Born in U.S.	.064	.031	.04
English Proficiency - ref: Speaks only English or speaks English well			
Speaks English not well or not at all	-.091	.038	.02
Race/Ethnicity - ref: Non-Hispanic White			
Latina/Hispanic	-.113	.031	<.01
NH Black	-.238	.041	<.01
Asian, AIAN, NHPI, Two or More Race	-.174	.037	<.01
Educational Attainment - ref: Less than BA/BS			
Has Bachelor's degree or higher	-.006	.025	.81
Household Income & Food Security - ref: 2nd and 3rd quartiles			
1st quartile	.116	.025	<.01
4th quartile	-.180	.031	<.01
Homeownership Status - ref: Rent or other arrangement			
Own home	-.082	.025	<.01
Employment Status - ref: Employed or not looking			
Unemployed	.197	.037	<.01
Insurance Status - ref: Currently uninsured or uninsured any time			
Insured all year	.018	.028	.51
Marital Status - ref: Married/living with partner			
Widowed/separated/divorced	.203	.027	<.01
Never married	.179	.030	<.01

	Coefficient	Standard Error[b]	p-value
Self-Reported Health - ref: Excellent, very good, or good health			
Fair or poor health	.671	.023	<.01
Chronic Conditions - No reported conditions			
Asthma, diabetes, &/or heart disease	.148	.023	<.01
Smoking Status - ref: Non-smoker			
Current smoker	.384	.027	<.01
Social Capita Score	-.076	.009	<.01
Perceived Safety - ref: Feels safe some or none of the time			
Feels safe in the neighborhood all or most of the time	-.172	.030	<.01
Presence of Children in Household - ref: No children in household			
Children in household	-.134	.030	<.01
Survey Year - ref: 2011			
2012	-.023	.030	.44
2013	.009	.031	.77
2014	-.020	.034	.55
2015	.030	.031	.33
Constant	-1.154	.076	<.01

Sources: California Health Interview Survey 2011, 2012, 2013, 2014, 2015; American Community Survey 2006-2010 and 2011-2015; Home Mortgage Disclosure Act Aggregate Data 2010 and 2015

[a] pseudo R^2=.15; mean VIF=1.5; GOF χ^2 (18) = 31.5; AUC=.79

[b] Robust standard errors were estimated to adjust for clustering in census tracts.

Table 3.6. Effect of Neighborhood Type on Past Year Serious Psychological Distress[a] by Tenure in Neighborhood, Homeownership Status, and Household Income, Adults Aged 18 and Over Living in Southern California Counties

	Tenure in Neighborhood		Homeownership Status		Household Income	
Neighborhood Type - ref: Low-income and not gentrified	**Recent residents n=15,884**	**Long-term residents n=17,165**	**Renters or other arrangement n=16,961**	**Homeowners n=26,854**	**Income <200% FPL n=14,840**	**Income 200% FPL+ n=28,975**
Low-income and gentrified	-.015 (.061)	.235** (.081)	.110* (.049)	.045 (.080)	.134** (.050)	.021 (.067)
Middle- to high-income and upscaled	.045 (.049)	.130* (.063)	.094* (.046)	.079 (.051)	.115* (.050)	.049 (.047)
Middle- to high-income and not upscaled	.015 (.039)	.110 (.054)	.037 (.034)	.078 (.045)	.047 (.035)	.043 (.041)

Sources: California Health Interview Survey 2011, 2012, 2013, 2014, 2015; American Community Survey 2006-2010 and 2011-2015; Home Mortgage Disclosure Act Aggregate Data 2010 and 2015

[a] Coefficients and robust standard errors (in parentheses) estimated from stratified probit models. Covariates in these models included respondent age, gender, race/ethnicity, marital status, education, tenure in the neighborhood, income, homeownership status, insurance status, English proficiency, overall health, chronic conditions, smoking status, perceived safety in the neighborhood, presence of children, social capita score, and year fixed-effects. Robust standard errors were estimated to adjust for clustering in census tracts.

** p<.01; * p<.05

Table 3.7. Descriptive Statistics of Exclusion Restriction Variables* Used in Propensity Score Analyses and Endogenous Treatment Effects Model Adults Aged 18 and Over Living in Low-Income Neighborhoods, n=12,246

	Median	Mean	SD	Min	Max
Percent Non-Hispanic White Residents (2010)	14.9	23.68	23.78	0	95.9
Median Household Income (2010)	$41,177	$41,373	$9,529	$13,130	$65,719

Sources: American Community Survey 2006-2010 and 2011-2015

* Exclusion restriction variables also included respondent race/ethnicity*percent of non-Hispanic White residents and respondent income level*median household income.

Table 3.8. Average Treatment Effects (ATEs) and Average Treatment Effects of the Treated (ATTs) from Propensity Score Matching and Inverse-Probability Weighting[a], Adults Aged 18 and Over Living in Low-Income Neighborhoods, n=12,246

	Estimate	Standard Error[b]	p-value
Propensity Score Matching			
ATE	.014	.007	.039
ATT	.017	.007	.010
Inverse-Probability Weighting			
ATE	.014	.007	.031
ATT	.009	.006	.124
Inverse-Probability Weighting with Regression Adjustment			
ATE	.014	.006	.024
ATT	.011	.006	.055

Sources: California Health Interview Survey 2011, 2012, 2013, 2014, 2015; American Community Survey 2006-2010 and 2011-2015; Home Mortgage Disclosure Act Aggregate Data 2010 and 2015

[a] Covariates (not shown) included respondent age, gender, race/ethnicity, marital status, education, tenure in the neighborhood, income, homeownership status, insurance status, English proficiency, overall health, chronic conditions, smoking status, perceived safety in the neighborhood, presence of children, social capita score, and year fixed-effects.

[b] Robust standard errors were estimated to adjust for clustering in census tracts.

Table 3.9. Endogenous Treatment Effects Model Results[a], Adults Aged 18 and Over Living in Low-Income Neighborhoods, n=12,246

	Coefficient	Standard Error[b]	p-value
Treatment Model: Neighborhood Gentrified			
Percent Non-Hispanic White Residents (2010)	0.011	0.003	<.01
Non-Hispanic White * % NH White	-0.004	0.003	0.22
Black * % NH White	-0.014	0.004	<.01
Asian, AIAN, NHPI, Two or More Race * % NH White	-0.010	0.003	<.01
Median Household Income (2010)	-1.06E-05	5.12E-06	0.04
Income 1st quartile * Median HH Income	-1.32E-05	3.94E-06	<.01
Income 4th quartile * Median HH Income	-2.99E-06	5.13E-06	0.56
Outcome Model: Past Year Serious Psychological Distress			
Neighborhood Type - ref: Low-income and not gentrified			
Low-income and gentrified	0.408	0.367	0.27
rho	-0.189	0.208	

Sources: California Health Interview Survey 2011, 2012, 2013, 2014, 2015; American Community Survey 2006-2010 and 2011-2015; Home Mortgage Disclosure Act Aggregate Data 2010 and 2015

[a] Covariates (not shown) included respondent age, gender, race/ethnicity, marital status, education, tenure in the neighborhood, income, homeownership status, insurance status, English proficiency, overall health, chronic conditions, smoking status, perceived safety in the neighborhood, presence of children, social capita score, and year fixed-effects. Wald test of rho=0; $\chi^2(1)=.787$; p=.375

[b] Robust standard errors were estimated to adjust for clustering in census tracts.

Table 3.10. Characteristics of Adults Aged 18 and Over Living in Low-Income Neighborhoods across Southern California by Gentrification Status, Original and Coarsened Exact Matching Samples

	Original Sample (n=12,597)		Matched* Sample (n=5,976)		Matched* & Weighted (n=6,083)	
	Gentrified n=3,123	Not Gentrified n=9,474	Gentrified n=1,848	Not Gentrified n=4,128	Gentrified n=1,848	Not Gentrified n=4,235
Outcome: Likely had serious psychological distress in the past year	9.2	9	9.3	9.2	9.3	8.6
Tenure in neighborhood						
1-5 years (recent resident)	43.5	46.3	42.9	44.6	42.9	44.6
6-14 years	25.8	24.9	24.8	24.8	24.8	23.7
15+ years (long-term resident)	30.8	28.8	32.4	30.6	32.4	31.6
Gender						
Female	59.5	59.9	61	59.3	61	59
Male	40.5	40.1	39	40.7	39	41
Age Category						
18-25	9.6	11.1	10.4	12.4	10.4	13.6
26-45	24	25.2	26	28	26	25.2
46-64	31.4	33.7	33.9	34	33.9	33.4
65+	34.9	30	29.7	25.6	29.7	27.9
Nativity						
Born outside U.S.	41.3	42.9	45.8	51	45.8	47.6
Born in U.S.	58.7	57.1	54.2	49	54.2	52.4
English Proficiency						
Speaks only English or speaks English well	75.3	72.1	70.3	65	70.3	68.6
Speaks English not well or not at all	24.7	27.9	29.7	35	29.7	31.4
Race/Ethnicity						
Latina/Hispanic	38.9	45.2	47.1	56.2	47.1	54.4

	Original Sample (n=12,597)		Matched* Sample (n=5,976)		Matched* & Weighted (n=6,083)	
	Gentrified n=3,123	**Not Gentrified n=9,474**	**Gentrified n=1,848**	**Not Gentrified n=4,128**	**Gentrified n=1,848**	**Not Gentrified n=4,235**
Non-Hispanic White	36.4	31.6	25.3	18	25.3	24.8
Black	9.6	10.1	12.8	13.4	12.8	10.7
Asian	12.6	10.6	12.2	10.5	12.2	8.5
AIAN, NHPI, Two or More Race	2.5	2.6	2.5	1.9	2.5	1.6
Has Bachelor's degree or higher	29.6	21.7	23.9	19.3	23.9	21.6
Household Income						
1st quartile	39.2	44.7	44.2	49.6	44.2	46.6
2nd and 3rd quartile	47.9	45.8	46.4	42.8	46.4	43.6
4th quartile	13	9.5	9.5	7.6	9.5	9.8
Homeownership Status						
Rent or other arrangement	59.7	60.4	62.5	64.7	62.5	63.1
Own home	40.3	39.6	37.5	35.3	37.5	36.9
Employment Status						
Employed or not looking	93.3	91.9	92.7	91.1	92.7	92.4
Unemployed	6.7	8.1	7.3	8.9	7.3	7.6
Insurance Status						
Currently uninsured or uninsured any time	20.1	23	22.7	25.9	22.7	24.4
Insured all year	79.9	77	77.3	74.1	77.3	75.6
Marital Status						
Married/living with partner	41.9	45.5	42.9	45.5	42.9	43.7
Widowed/separated/divorced	32.5	29.9	30.1	27.4	30.1	28
Never married	25.5	24.6	26.9	27.1	26.9	28.3
Reported fair or poor health	29.2	34	31.6	36.6	31.6	34.4
Chronic Conditions						

	Original Sample (n=12,597)		Matched* Sample (n=5,976)		Matched* & Weighted (n=6,083)	
	Gentrified n=3,123	Not Gentrified n=9,474	Gentrified n=1,848	Not Gentrified n=4,128	Gentrified n=1,848	Not Gentrified n=4,235
No reported conditions	67.9	67.6	68.1	68.7	68.1	68.3
Asthma, diabetes, &/or heart disease	32.1	32.4	31.9	31.3	31.9	31.7
Current smoker	12.2	13.6	11.3	12.8	11.3	11.6
Social Capita Score						
2	1.2	2.1	1.4	2.3	1.4	2.4
3	2.7	2.6	2.5	2.6	2.5	2.7
4	12.1	13.8	13.9	16.1	13.9	14.1
5	16.6	18.3	17.5	19.8	17.5	19.2
6	46.7	45.1	47.8	43.7	47.8	45.4
7	12.3	10.7	10.4	9.5	10.4	9.2
8	8.5	7.4	6.4	6.1	6.4	7
Feels safe in the neighborhood all or most of the time	82.5	78.1	78.4	73.9	78.4	75.2
Children in household	21.3	26.3	24.4	29.4	24.4	27.6

Sources: California Health Interview Survey 2011, 2012, 2013, 2014, 2015; American Community Survey 2006-2010 and 2011-2015; Home Mortgage Disclosure Act Aggregate Data 2010 and 2015

* Respondents in gentrified and not-gentrified neighborhoods were matched on the four neighborhood characteristics: 1) percent of non-Hispanic White residents in 2006-2010, 2) percent of residents in poverty in 2006-2010, 3) change in percent of non-Hispanic White residents from 2000 to 2010, and 4) change in percent of residents in poverty from 2000 to 2010.

Table 3.11. Results[a] of Weighted Probit Model with Endogenous Neighborhood Upscaling Score, Matched Adults Aged 18 and Over Living in Low-Income Neighborhoods, n=6,066

	Coefficient	Standard Error[b]	p-value
First stage: Upscaling Score			
Neighborhood Type - ref: Low-income and not gentrified			
Low-income and gentrified	0.871	0.138	0.00
Constant	-0.120	0.251	0.63
Second Stage: Serious Psychological Distress			
Predicted upscaling score	0.088	0.079	0.27
Constant	-1.767	0.257	0.00
Estimate of rho	-0.057	0.093	0.54
ln(sigma)	0.061	0.159	0.70
Correlation(e.upscaling score, e.spd)	-0.057	0.093	

Sources: California Health Interview Survey 2011, 2012, 2013, 2014, 2015; American Community Survey 2006-2010 and 2011-2015; Home Mortgage Disclosure Act Aggregate Data 2010 and 2015

[a] Covariates (not shown) included respondent age, gender, race/ethnicity, marital status, education, tenure in the neighborhood, income, homeownership status, insurance status, English proficiency, overall health, chronic conditions, smoking status, perceived safety in the neighborhood, presence of children, social capita score, and year fixed-effects. Wald test of exogeneity; $\chi^2(1)=.37$; p=.542

[b] Robust standard errors were estimated to adjust for clustering in census tracts.

Table 3.12. Descriptive Statistics of Candidate Instrumental Variables for Gentrification, n=12,067

	Median	Mean	SD	Min	Max
Neighborhood distance (miles) to nearest rail station	3.58	4.73	5.29	0.07	90.47
Neighborhood distance (miles) to nearest high-income census tract	2.11	5.09	1.28	0.03	111.56
Difference in mean similar and overall school ranks of public elementary schools in neighborhood (and interaction with whether children are in household)	1.43	2.31	2	-8	6
Percent renter-occupied housing units in neighborhood	62.57	21.27	64.60	4.00	99.60

Sources: California Department of Education 2010; National Center for Education Statistics (NCES) School Attendance Boundary Survey 2010-2011 and 2013-2014; California Department of Transportation 2013

Table 3.13. Results from Instrumental Variables Estimation[a] for Past Year Serious Psychological Distress, Adults Aged 18 and Over Living in Low-Income Neighborhoods, n=12,067

	Two-Stage Least Squares		Two-Stage Residual Inclusion		Seemingly Unrelated Bivariate Probit	
First Stage: Treatment model for gentrified neighborhood	**b**	**SE[b]**	**b**	**SE**	**b**	**SE**
Children in household x Difference in ranks						
Children not in household x difference	-0.001	0.007	-0.003	0.022	-0.004	0.022
Children in household x difference	0.015*	0.007	0.053*	0.024	0.052*	0.026
Distance to nearest high-income census tract	-0.006**	0.001	-0.095**	0.029	-0.095**	0.029
Second Stage: Outcome model for past year SPD	**b**	**SE**	**b**	**SE**	**b**	**SE**
Neighborhood Type - ref: Low-income and not gentrified						
Low-income and gentrified	-0.042	0.059	-0.289	0.354	0.336	1.513

Sources: California Health Interview Survey 2011, 2012, 2013, 2014, 2015; American Community Survey 2006-2010 and 2011-2015; Home Mortgage Disclosure Act Aggregate Data 2010 and 2015; National Center for Education Statistics (NCES) School Attendance Boundary Survey 2010-2011 and 2013-2014; California Department of Transportation

[a] Covariates (not shown) included respondent age, gender, race/ethnicity, marital status, education, tenure in the neighborhood, income, homeownership status, insurance status, English proficiency, overall health, chronic conditions, smoking status, perceived safety in the neighborhood, presence of children, social capita score, and year fixed-effects.

[b] Robust standard errors were estimated to adjust for clustering in census tracts.

** p<.01; * p<.05

Table 3.14. Average Marginal Effects or Average Treatment Effects for All Models and Approaches[a], Adults Aged 18 and Over Living in Low-Income Neighborhoods

	Estimate	Standard error[b]
Ordinary Least Squares	0.012*	0.006
Probit	0.011*	0.005
Propensity Score Matching	0.014*	0.007
Inverse-Probability Weighting	0.014*	0.007
Inverse-Probability Weighting with Probit Regression Adjustment	0.014*	0.006
Endogenous Treatment Effects (Seemingly Unrelated Bivariate Probit)	0.067	0.069
Neighborhood Matching & Probit Regression with Endogenous Covariate	0.005	0.011
Instrumental Variables Estimation		
Two-Stage Least Squares	-0.042	0.059
Two-Stage Residual Inclusion (Probit)	-0.027	0.070
Seemingly Unrelated Bivariate Probit	0.053	0.269

Sources: California Health Interview Survey 2011, 2012, 2013, 2014, 2015; American Community Survey 2006-2010 and 2011-2015; Home Mortgage Disclosure Act Aggregate Data 2010 and 2015; Census 2000 and 2010; California Department of Education 2010; National Center for Education Statistics (NCES) School Attendance Boundary Survey 2010-2011 and 2013-2014; California Department of Transportation

[a] Covariates (not shown) included respondent age, gender, race/ethnicity, marital status, education, tenure in the neighborhood, income, homeownership status, insurance status, English proficiency, overall health, chronic conditions, smoking status, perceived safety in the neighborhood, presence of children, social capita score, and year fixed-effects.

[b] Robust standard errors were estimated to adjust for clustering in census tracts.

** p<.01; * p<.05

Table 3.15. Average Marginal Effects or Average Treatment Effects for All Models and Approaches[a] Using Three Different Measures of Neighborhood Change, Adults Aged 18 and Over Living in Low-Income Neighborhoods

	Strategy for Classifying Neighborhood Change		
	Principal Components Analysis	K-Medians Cluster Analysis	Threshold Strategy
	Estimate (SE[b])	Estimate (SE)	Estimate (SE)
Ordinary Least Squares	0.012* (0.006)	-.014* (.007)	.004 (.007)
Probit	0.011* (0.005)	-.011 (.006)	.002 (.005)
Propensity Score Matching	0.014* (0.007)	-.012 (.009)	.004 (.008)
Inverse-Probability Weighting	0.014* (0.007)	-.014 (.008)	.013 (.008)
Inverse-Probability Weighting with Probit Regression Adjustment	0.014* (0.006)	-.014 (.008)	.011 (.008)
Endogenous Treatment Effects (Probit)	0.067 (0.069)	.0004 (.038)	-.029 (.035)
Neighborhood Matching & Probit Regression with Endogenous Covariate	0.005 (0.011)	.003 (.010)	.003 (.010)
Instrumental Variables Estimation			
Two-Stage Least Squares	-0.042 (0.059)	.032 (.105)	-.040 (.242)
Two-Stage Residual Inclusion (Probit)	-.027 (.070)	-.014 (.029)	-.014 (.120)

Sources: California Health Interview Survey 2011, 2012, 2013, 2014, 2015; American Community Survey 2006-2010 and 2011-2015; Home Mortgage Disclosure Act Aggregate Data 2010 and 2015; Census 2000 and 2010; California Department of Education 2010; National Center for Education Statistics (NCES) School Attendance Boundary Survey 2010-2011 and 2013-2014; California Department of Transportation

[a] Covariates (not shown) included respondent age, gender, race/ethnicity, marital status, education, tenure in the neighborhood, income, homeownership status, insurance status, English proficiency, overall health, chronic conditions, smoking status, perceived safety in the neighborhood, presence of children, social capita score, and year fixed-effects.

[b] Robust standard errors were estimated to adjust for clustering in census tracts.

** p<.01; * p<.05

Table 3.16. Probit Regression Results[a] Using Neighborhood Change Indicators as Key Independent Variables, Adults Aged 18 and Over Living in Low-Income Neighborhoods

	All Respondents n=12,246	Recent residents n=5,580	Long-term residents n=3,592	Renters n=7,366	Homeowners n=4,880	Income <200% FPL n=6,787	Income 200% FPL+ n=5,459
Standardized-unit change[b] in…	**Estimate (SE[c])**	**Estimate (SE)**	**Estimate (SE)**	**Estimate (SE)**	**Estimate (SE)**	**Estimate (SE)**	**Estimate (SE)**
Improvement loans per capita (2015 dollars)	-0.001 (0.046)	-0.066 (0.063)	0.112 (0.073)	-0.005 (0.056)	-0.017 (0.089)	0.038 (0.058)	-0.086 (0.066)
Median household income (2015 dollars)	0.057 (0.037)	0.032 (0.054)	0.025 (0.085)	0.053 (0.045)	0.050 (0.077)	0.018 (0.047)	0.129* (0.057)
Median home value (2015 dollars)	-0.005 (0.018)	-0.041 (0.026)	0.110** (0.036)	-0.015 (0.021)	0.027 (0.043)	0.001 (0.020)	-0.016 (0.031)
Loans originated for conventional home purchases (2015 dollars)	0.009 (0.011)	0.018 (0.022)	0.003 (0.013)	0.015 (0.012)	-0.012 (0.026)	0.001 (0.011)	0.027 (0.024)
Median gross rent (2015 dollars)	-0.011 (0.035)	0.100* (0.050)	-0.141 (0.077)	0.000 (0.043)	-0.043 (0.067)	-0.036 (0.047)	0.036 (0.054)
Proportion of middle- to high-income residents	-0.003 (0.021)	-0.023 (0.030)	0.077 (0.041)	0.006 (0.025)	-0.027 (0.037)	0.024 (0.025)	-0.065 (0.035)
Proportion of adults (aged 25+) with a college degree	0.046* (0.020)	0.014 (0.026)	0.066 (0.040)	0.026 (0.022)	0.098* (0.043)	0.027 (0.024)	0.066* (0.034)
Proportion of non-Hispanic White residents	-0.053** (0.020)	-0.063* (0.026)	-0.062 (0.045)	-0.031 (0.025)	-0.101** (0.037)	-0.016 (0.027)	-0.088** (0.030)

Sources: California Health Interview Survey 2011, 2012, 2013, 2014, 2015; American Community Survey 2006-2010 and 2011-2015; Home Mortgage Disclosure Act Aggregate Data 2010 and 2015; Census 2000 and 2010; California Department of Education 2010; National Center for Education Statistics (NCES) School Attendance Boundary Survey 2010-2011 and 2013-2014; California Department of Transportation

[a] Covariates (not shown) included respondent age, gender, race/ethnicity, marital status, education, tenure in the neighborhood, income, homeownership status, insurance status, English proficiency, overall health, chronic conditions, smoking status, perceived safety in the neighborhood, presence of children, social capita score, and year fixed-effects.

[b] Changes between 2006-2010 and 2011-2015 were standardized by county. Coefficients represent the average change associated with a one standard deviation increase in each indicator.

[c] Robust standard errors were estimated to adjust for clustering in census tracts.

** $p<.01$; * $p<.05$

Supplemental Materials

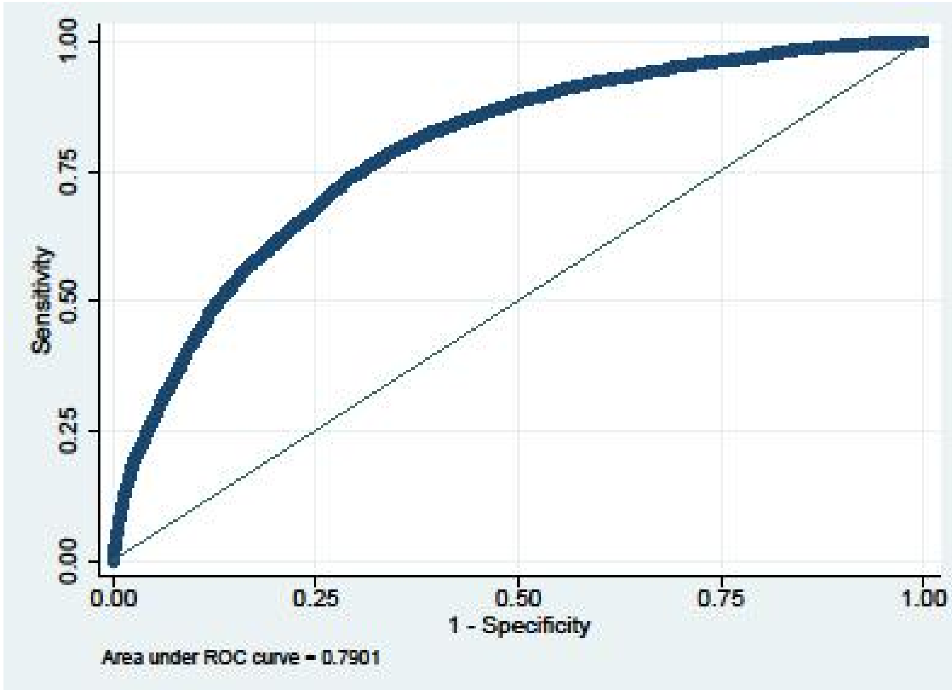
Table 3.S1. Measurement Model for Serious Psychological Distress

Risk Category	Construct	Measure (variable type)	Direction of Association	Rationale
Demographic	Gender minority status	Male (binary)	Positive	Women have greater risk for SPD than men.
	Life stage	Age (categorical)	Varies	Seniors have lower risk for SPD than younger groups.
	Social position (nativity)	Born in US (binary)	Negative	U.S. born citizens are likely to feel more secure in their residential status than immigrants and therefore have fewer stressors, all else constant.
	Linguistic isolation	Limited English proficiency (binary)	Positive	Linguistic isolation can limit individuals' access to resources and lead to SPD.
	Social position (racial/ethnicity)	Race/ethnicity (categorical)	Varies	Asians have lower odds of SPD compared to NH Whites. Prevalence of SPD is higher among Hispanic/Latina and Black people than among White people.
Socioeconomic status	Socioeconomic status	Bachelor's degree or higher (binary)	Negative	People with higher education have or believe to have job/financial security compared to those with less education. Higher education can also increase social capital, which is protective against SPD.
	Socioeconomic status	Family income to poverty threshold ratio (continuous)	Negative	People with higher incomes have greater access to resources that prevent or help them cope with psychological distress.

Risk Category	Construct	Measure (variable type)	Direction of Association	Rationale
	Wealth	Own home (binary)	Negative	People who own their homes have equity, which can be used to meet needs. Renters do not have this option.
Financial stressors	Source of income	Unemployed looking for work (indicator)	Positive	Unemployed people are less likely to have a stable source of income and are more likely to experience financial strain and SPD.
	Access to health care	Insured throughout year (binary)	Negative	Insured people have greater access to care and less worries about financial strain related to health care.
	Food security	Food insecurity with or without hunger (binary)	Positive	Food insecurity is a clear sign of financial strain, which increases adults' risk of poor health and SPD.
Social support		Presence of children		
	Emotional support	Marital status (categorical)	Positive	Married people, on average, have emotional support from their partners, which help protect against psychological distress.
Health status	Self-reported general health	Fair or poor health (binary)	Positive	People with poor health are more likely to experience psychological distress compared to people with good to excellent health.
	Presence of chronic conditions	Doctor ever told you have asthma, diabetes, heart disease (binary)	Positive	People with chronic conditions are more likely to experience psychological distress compared to people with good to excellent health.
	Risk behaviors	Current smoker (binary)	Positive	Smokers have higher levels of SPD. Adults with SPD are also more likely to be smokers.

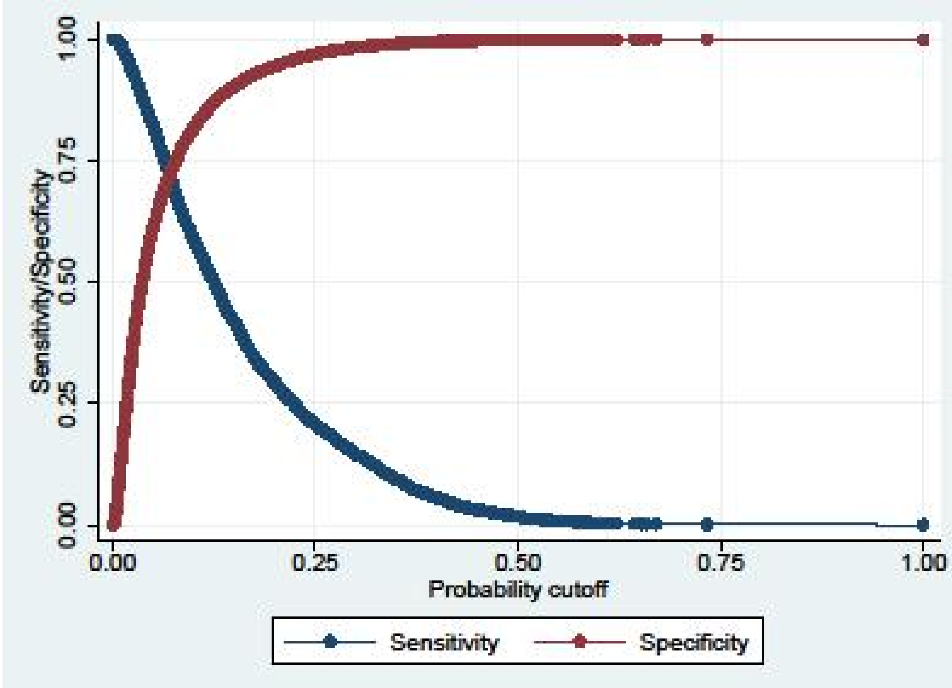
Risk Category	Construct	Measure (variable type)	Direction of Association	Rationale
Neighborhood stressors	Social capital	Social capital score (count)	Negative	People with more social capital have greater access to social support, opportunities, and resources that help protect against psychological distress.
	Perception of safety	Feels safe in neighborhood some or none of the time (binary)	Positive	Safety is important for psychological well-being. People who do not feel safe in their neighborhoods may be more distressed.
	Gentrification *(key independent variable)*	Neighborhood change (categorical)	Positive	Rapid changes in the physical, economic, and social characteristics of a neighborhood can increase financial stressors, stir community tensions, and raise fears of displacement among residents.

Figure 3.S1. Receiver Operating Characteristic (ROC) Curve for Probit Model of Past Year Serious Psychological Distress, Adults Aged 18 and Over Living in Southern California Counties, n=43,815



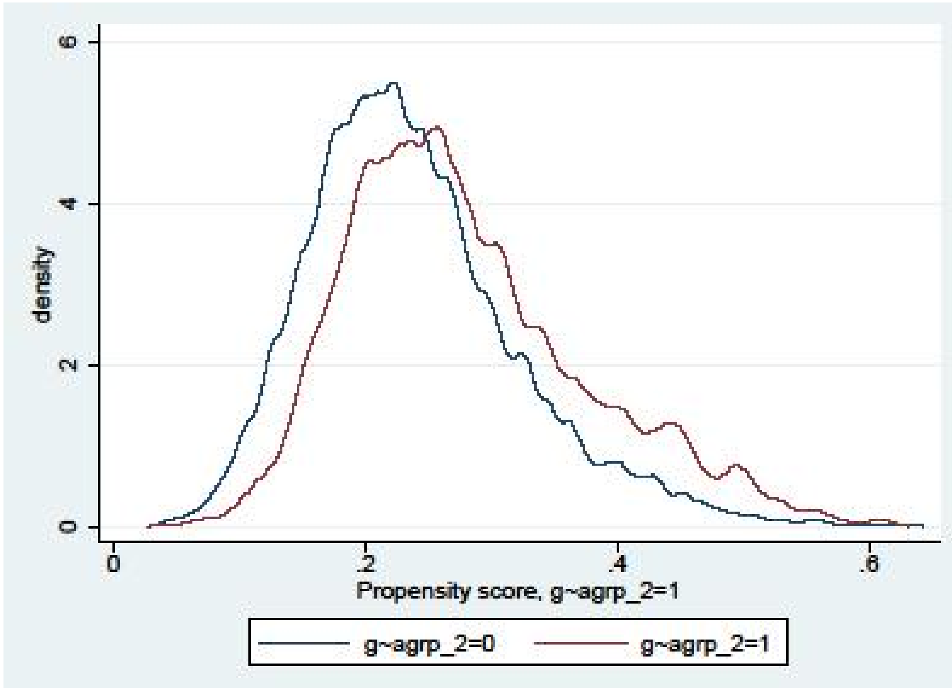
Sources: California Health Interview Survey 2011, 2012, 2013, 2014, 2015; American Community Survey 2006-2010 and 2011-2015; Home Mortgage Disclosure Act Aggregate Data 2010 and 2015

Figure 3.S2. Sensitivity and Specificity by Probability Cutoff for Probit Model of Past Year Serious Psychological Distress, Adults Aged 18 and Over Living in Southern California Counties, n=43,815



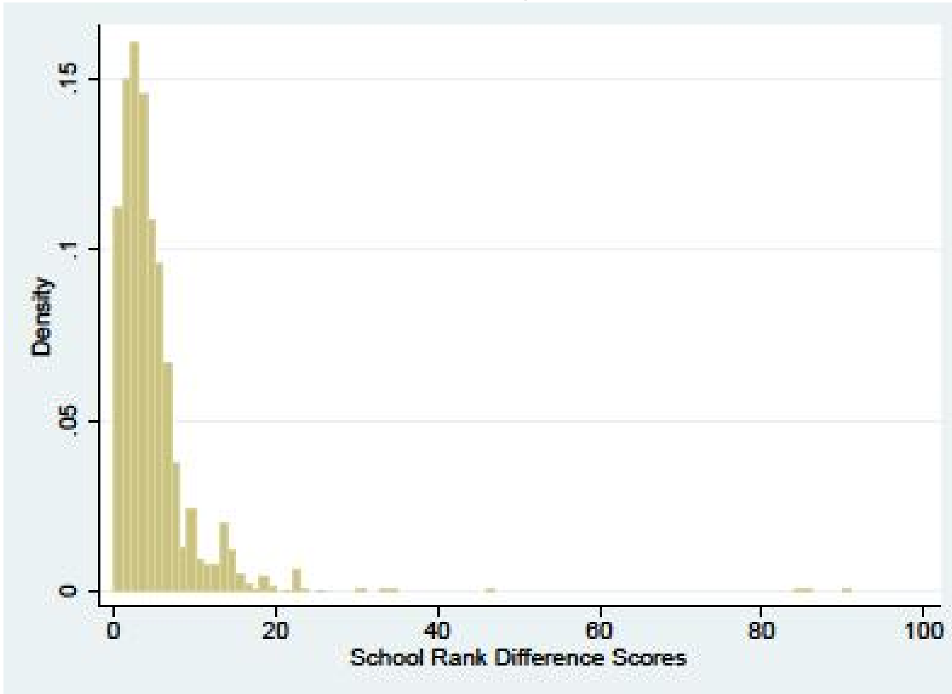
Sources: California Health Interview Survey 2011, 2012, 2013, 2014, 2015; American Community Survey 2006-2010 and 2011-2015; Home Mortgage Disclosure Act Aggregate Data 2010 and 2015

Figure 3.S3. Histogram (Density) of Propensity Scores for Respondents Living in Low-Income and Gentrified Neighborhoods and Respondents in Low-Income and Not Gentrified Neighborhoods, n=12,246



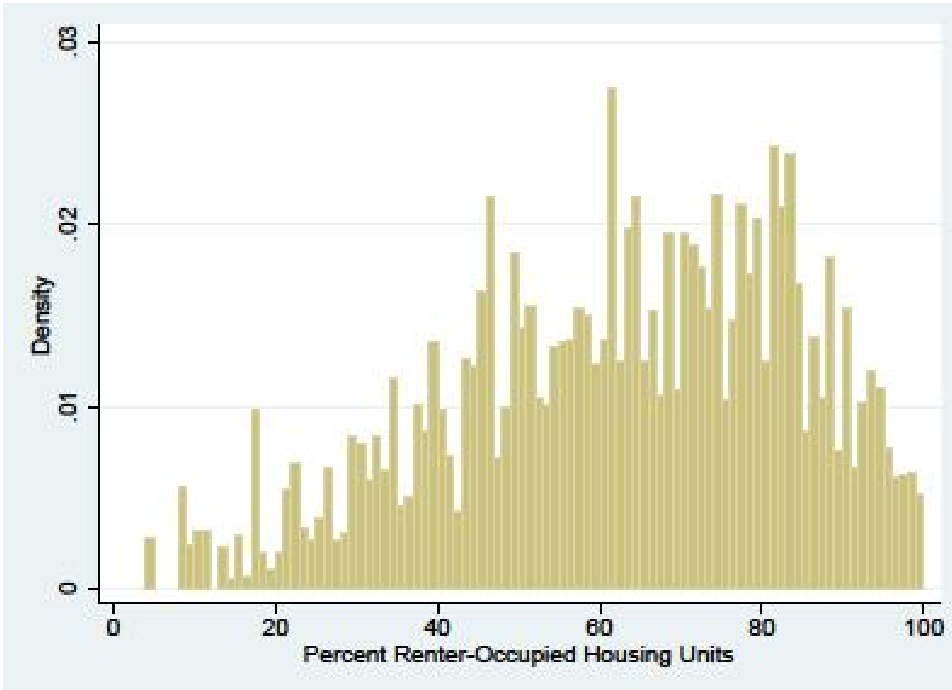
Sources: California Health Interview Survey 2011, 2012, 2013, 2014, 2015; American Community Survey 2006-2010 and 2011-2015; Home Mortgage Disclosure Act Aggregate Data 2010 and 2015
Propensity scores were estimated using a probit model predicting likelihood of living in a gentrified neighborhood on percent residents who were non-Hispanic White, median household income, respondent race/ethnicity*percent non-Hispanic residents, respondent income category*median household income, a set of individual covariates associated with the outcome, and year-fixed effects.

Figure 3.S4. Distribution of Neighborhood's Distance (Miles) to Nearest Rail Station, Adults Aged 18 and Over in Low-Income Neighborhoods, n=12,246



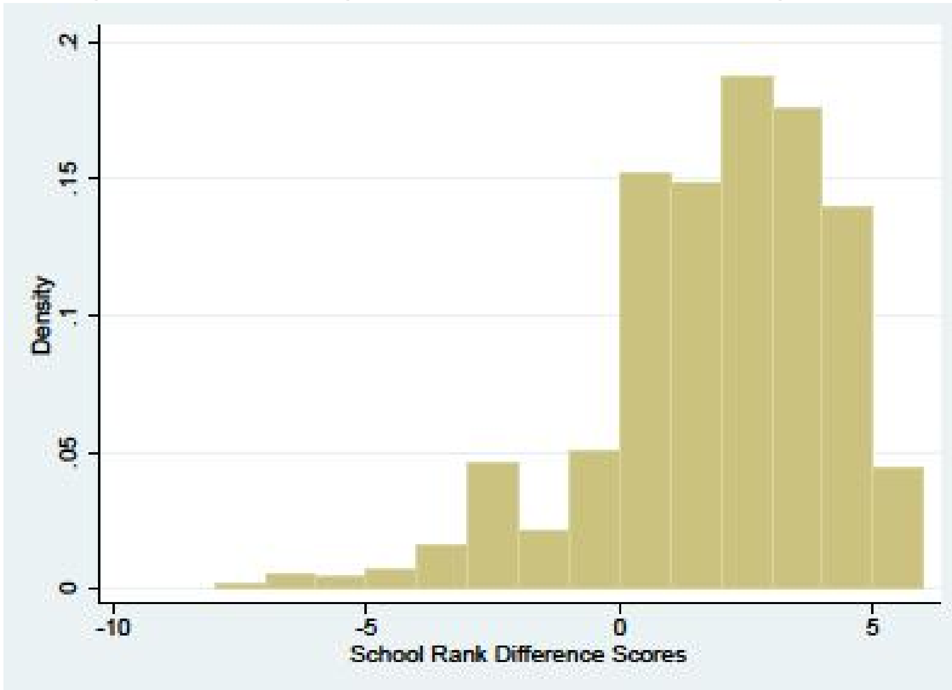
Source: California Department of Transportation 2013

Figure 3.S5. Distribution of Percent of Renter-Occupied Housing Units Neighborhood, Adults Aged 18 and Over in Low-Income Neighborhoods, n=12,246



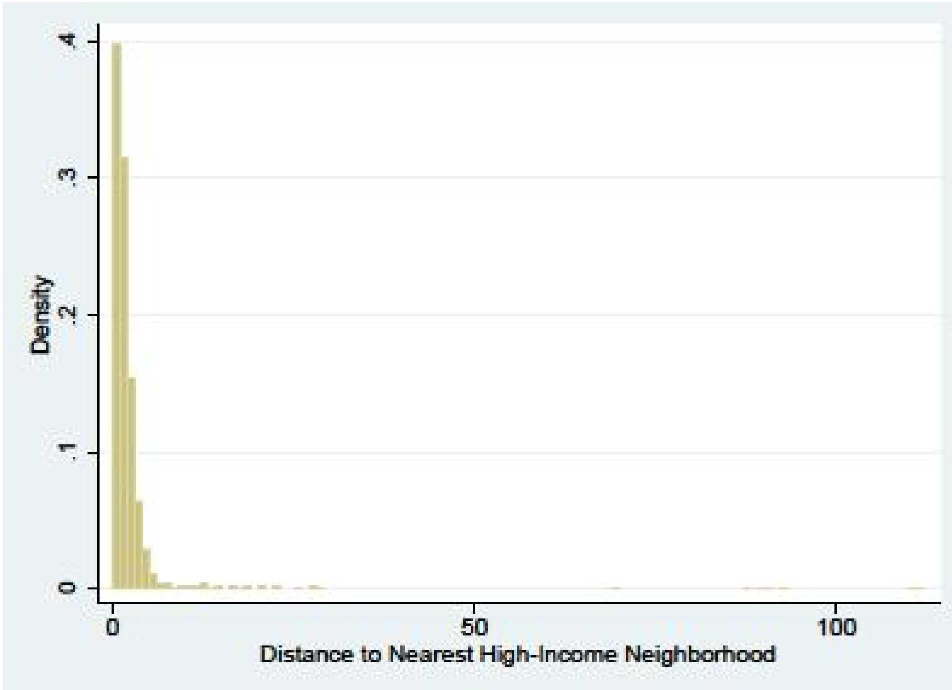
Source: American Community Survey 2006-2010

Figure 3.S6. Distribution of Difference in Mean Similar and Overall School Ranks of Public Elementary Schools in Neighborhood, Adults Aged 18 and Over in Low-Income Neighborhoods, n=12,067



Sources: California Department of Education 2010; National Center for Education Statistics (NCES) School Attendance Boundary Survey 2010-2011 and 2013-2014

Figure 3.S7. Distribution of Neighborhood's Distance (Miles) to Nearest High-Income Neighborhood, Adults Aged 18 and Over in Low-Income Neighborhoods, n=12,246



Source: American Community Survey 2006-2010

Chapter 4: Displacement Within Gentrified Neighborhoods

Introduction

Gentrification is the rapid upscaling of historically under-resourced neighborhoods. Gentrified neighborhoods experience accelerated and substantial physical restructuring (e.g., improved roads and sidewalks, parklets, etc.), economic growth, and social and cultural shifts. Gentrification contributes to rising home and commercial prices, which can increase wealth for homeowners but also deplete the financial resources of renters paying higher rents (Atkinson, 2002; Lance Freeman, 2006). Gentrified neighborhoods often experience expanded food and retail options, the benefits of which may be inaccessible to residents with lower incomes because new businesses often cater to middle-class residents (Deener, 2007; S. Zukin et al., 2009). Gentrified neighborhoods also undergo rapid social and cultural change, which can disrupt longtime residents' sense of belonging, and in the case of residential displacement, sever residents' social networks (Burns et al., 2012; Lees et al., 2008). In-migration of new residents, many of whom are more educated and have higher incomes than original residents, shifts the character of gentrifying neighborhoods, which are exacerbated when gentrification drives displacement of original residents (L. Freeman, 2005). Residential displacement is cause for concern because the poorest residents would bear the greatest costs of gentrification.

Gentrification has been linked to residential displacement, which according to George and Eunice Grier (1978), "occurs when any household is forced to move from its residence by conditions that affect the dwelling or its immediate surroundings, and that: 1) are beyond the household's reasonable ability to control or prevent; 2) occur despite the household's having met all previously imposed conditions of occupancy; and 3) make continued occupancy by that household impossible, hazardous, or unaffordable." Direct displacement refers to situations in which households are forced, whether by physical or economic pressure, to leave their current residences (Marcuse, 1985). Exclusionary displacement occurs when households are prevented from moving into housing units because changes in the neighborhood beyond their control have made living in the unit impossible or unaffordable. Quantitative studies examining the relationship between gentrification and displacement have produced mixed results, which is partially due to inconsistency in definitions and approaches employed, but suggest that displacement from gentrified neighborhoods is more moderate than expected (Zuk et al., 2015).

One explanation for low displacement and mobility rates in gentrified neighborhoods is the use of census tracts to represent neighborhoods, which potentially masks displacement (McKinnish et al., 2010). A second reason is residents' efforts to remain in gentrifying neighborhoods. Residents may be willing to pay higher living costs given the positive changes they observe in their neighborhoods, or "double up" and move in with friends and relatives to reduce their housing burden (Ding et al., 2016; L. Freeman & Braconi, 2004; Newman & Wyly, 2006). In the latter scenario, moving to a new residence in the same neighborhood because the current unit has become unaffordable may be considered a form of within-neighborhood displacement. Although these residents managed to remain in their neighborhoods, the costs associated with moving, changes in housing conditions and quality, and lingering fears of displacement will likely have an impact on their mental health.

Few studies have examined the relationships between gentrification, displacement, and health. The downstream effects of the costs and benefits of gentrification, including pathways through which gentrification impacts adult mental health, are not fully understood. Gentrification has been linked to poorer health ratings and elevated risks for preterm birth for residents of color (Gibbons & Barton, 2016; Huynh & Maroko, 2014). In a cohort study, residents displaced from gentrified neighborhoods had higher rates of emergency department visits, hospitalizations, and mental health-related visits compared to residents who remained in gentrified neighborhoods (Lim et al., 2017). The relationship between within-neighborhood displacement and mental health is unknown. Expanding knowledge in this area is particularly important for people with low incomes, who are already at increased risk for serious psychological distress.

Neighborhoods are open systems, and movement in and out of neighborhoods is nonrandom. In order to gain a comprehensive understanding of whether and how gentrification impacts mental health, researchers must be able to observe and compare in-movers new to gentrified and not gentrified neighborhoods, out-movers who exited their neighborhoods, and non-movers or pre-existing residents who had lived in their communities prior to gentrification and had stayed. Researchers must also observe the mental health statuses of these resident groups at multiple time periods: prior to, during, and after gentrification and moving. This requires a longitudinal study that tracks participants' movement in and out of neighborhoods and collects repeated measures of mental health status. Such data were not adequate or available at the time of this study. Although out-movers were not observed in the dataset, we harnessed questions related to moving in the California Health Interview Survey (CHIS) to better understand the characteristics of in-movers, their reasons for moving, and how similar they are to non-movers in gentrified and not gentrified neighborhoods. We also identified another set of residents: within-neighborhood movers or people who moved from one residential unit to another within the same neighborhood. Attributes and motivations for moving for this group were previously unknown.

Our study focused on intra-neighborhood mobility and explored the potential mental health consequences of within-neighborhood displacement. Specifically, we compared within-neighborhood movers and non-movers in gentrified neighborhoods and not gentrified neighborhoods, and assessed the impact of moving due to unaffordable housing on adult mental health. Our study examined the following research questions:

1) Does moving within the same neighborhood increase risk for serious psychological distress? If so, is the effect of moving within the same neighborhood on SPD moderated by whether residents lived in gentrified or not gentrified neighborhoods?
2) Does gentrification trigger within-neighborhood displacement, and does displacement affect adult mental health? To examine this question, we tested three additional questions.
    a. Are adults who moved within gentrified neighborhoods more likely to move because of unaffordable housing than similar adults who moved in not gentrified neighborhoods?
    b. Does moving due to unaffordable housing, relative to moving for other reasons, impact respondents' likelihood for serious psychological distress?
    c. Among adults who recently moved within the same neighborhoods, does living in a gentrified neighborhood increase likelihood of serious psychological distress compared to living in a not gentrified neighborhood?

We surmised that stressors associated with moving is associated with greater risk for serious psychological distress (SPD) compared to non-movers. We also hypothesized that residents of gentrified neighborhoods more often experienced high housing burden and were therefore at greater risk for within-neighborhood displacement. We anticipated that within-neighborhood displacement increased respondents' likelihood for SPD and mediated the impact of moving within a gentrified neighborhood, relative to moving within a not gentrified neighborhood. Figure 4.1 is a graphical representation of the relationships examined in research question 2. We should emphasize that without knowing whether respondents had SPD prior to gentrification, we cannot measure how gentrification affects residents' mental health over time. Estimates reported in this study represent associations and should be interpreted with these considerations in mind.

Methods

Data Sources. This study used five years from the California Health Interview Survey (CHIS) (years 2011, 2012, 2013, 2014, 2015). The initial sample had 104,209 adult respondents aged 18 and over, 45,917 of whom lived in six select Southern California counties: Ventura, Los Angeles, Orange, San Bernardino, Riverside, and San Diego. Responses from interviewees who completed the survey by proxy were excluded. Respondents who lived in rural census tracts or in tracts with fewer than 500 residents were also excluded. Census tract-level measures of neighborhood gentrification were merged with CHIS responses using census tract Federal Information Processing Standards (FIPS) codes, and 44,905 of 45,652 (98.4%) CHIS observations were successfully merged.

Of the 43,815 respondents with non-missing data, 29% (n=12,463) of had lived at their current addresses for less than five years. We then identified adults who recently moved within the same neighborhood by comparing the length of time respondents reported living in their current neighborhoods versus at their current addresses. (Only respondents who had lived at their current address for less than five years were asked the length of time lived in the current neighborhood.) Respondents who had lived in their neighborhoods for longer periods than at their current residences were considered to have recently moved within the same neighborhood. Our analyses focused on the 12,463 adult respondents who moved within the past five years as well as the subset of 2,561 within-neighborhood movers, or respondents who moved from one residence to another in the same neighborhood. See Figure 4.2 for an illustration of how we identified within-neighborhood movers.

In order to observe the potential impact of moving on SPD, we created a non-mover group. Non-movers had lived at their current residences for over five years. We only selected non-movers who lived in the same neighborhoods (census tracts) of the 2,561 within-neighborhood movers. Limiting the non-mover population to these neighborhoods allowed us to compare movers and non-movers in the same neighborhoods, movers and non-movers in gentrified and not gentrified neighborhoods, and any interaction between moving and gentrification status. There were 14,696 non-movers who lived in the same neighborhoods as respondents who moved to the same neighborhoods.

Measures. The primary outcome was an indicator for serious psychological distress (SPD) in the past year. SPD was assessed using the Kessler 6, a 6-item assessment tool designed to estimate the prevalence of adults with non-specific psychological distress (Kessler et al., 2002). Respondents were asked to reflect on the worst month in the past year and indicate how often they felt nervous, hopeless, restless or fidgety, worthless, that everything was an effort, and so depressed that nothing can cheer them up. Respondents answered “All of the time,” “most of the time,” “some of the time,” “a little of the time,” or “none of the time.” Responses were converted to scores and respondents with Kessler 6 scores of 13 and above (range 0 to 24) were categorized as having serious psychological distress in the past year.

The first key independent variable was an indicator for living in a low-income and gentrified neighborhood. To construct this measure, we used data from the 2006-2010 American Community Survey, 2011-2015 American Community Survey, and 2010 and 2015 Home Mortgage Disclosure Act (HMDA) aggregate reports and identified eight indicators representing physical structuring, economic growth, and cultural shifts in neighborhoods. See Chapter 2 for details. We then created a composite score for neighborhood upscaling and categorized census tracts as “Low-income and gentrified,” “Low-income and not gentrified,” “Middle- to high-income and upscaled,” or “Middle- to high-income and not upscaled.” We merged this variable to CHIS responses using the census tract FIPS codes corresponding to respondents’ residences and collapsed the variable into two categories: “Low-income and gentrified” and “Not gentrified.” We also categorized movers and non-movers by the gentrification status of their neighborhoods and created a variable with four comparison groups: “Mover within gentrified neighborhood,” “Non-mover within gentrified neighborhood,” “Mover within not gentrified neighborhood," and "Non-mover within not gentrified neighborhood." Table 4.1 presents the four comparison groups that we focused on to assess research question 1.

The second key independent variable was an indicator for having moved residences due to unaffordable housing. Respondents were asked to identify the main reason they moved from their last residence, and those who reported that they "couldn't afford the rent or mortgage" reasons were defined as having moved due to unaffordable housing. Respondents who moved because of "other housing-related" reasons, a "change in marital/relationship status", "to establish own household," "for child's education," "to attend or leave college," for "work-related" reasons, for "better neighborhood/less crime", or "other" reasons were categorized as having moved for other reasons. Although moving because of a change in relationship status or for work-related reasons could be considered negative in some situations, we focused on housing-related push factors because direct residential displacement more likely functions through rent increases and other housing conditions that make continued occupancy unfeasible. Residents who recently moved from one residence to another in the same neighborhood due to unaffordable housing were considered to have experienced "within-neighborhood displacement."

Figure 4.2 depicts how movers and non-movers were identified and categorized using CHIS. Note that the prior neighborhoods or census tracts of respondents who moved to the same neighborhoods were known—their current neighborhoods were also their prior neighborhoods. For respondents who moved to different neighborhoods, their prior neighborhoods were unknown, which limited our ability to track their mobility patterns.

Covariates measured socioeconomic position and other factors that potentially confound the relationship between our key independent variables and serious psychological distress. These covariates included demographic factors (age, gender, race/ethnicity, nativity, and English language proficiency), socioeconomic status (education, household income category, and homeownership), financial stressors (employment status and insurance status), social support (marital and parental status), health status (self-reported health, smoking status, and presence of chronic conditions), and neighborhood stressors (social capital and perception of neighborhood safety).

Analyses. Descriptive statistics summarized all variables by mover and neighborhood gentrification status. We then predicted the probability of SPD with a categorical variable that indicated whether respondents moved or did not move within gentrified or not gentrified neighborhoods (the reference category was non-movers in not gentrified neighborhoods), a set of individual covariates, and year fixed-effects. We repeated the probit regression across three different samples: 1) within-neighborhood movers and non-movers living in the same neighborhoods as movers (n=17,257), 2) within-neighborhood movers and non-movers living in low-income neighborhoods (neighborhoods with median incomes below 80% of their respective counties' median household incomes) (n=8,823), and 3) within-neighborhood movers living in low-income neighborhoods and non-movers living in the same neighborhoods as movers (n=5,218). Average marginal effects were calculated to estimate the effect of not moving and moving within gentrified neighborhoods on likelihood of SPD, relative to not moving from a not gentrified neighborhood. To understand the potential impacts living and moving within gentrified neighborhoods had on the mental health of renters with low incomes—residents at greatest risk of direct residential displacement—,we also estimated predictive margins for renters with household incomes in the 1st quartile across the four comparison groups. The probit model specifications for research question 1 are as follows:

$$y_i^* = \alpha_i + \beta M_i + X_i\beta + \varepsilon_i$$

$$\varepsilon \sim N(0,1)$$

$$y_i = \begin{Bmatrix} 1 \text{ if } y^* > 0 \\ 0 \text{ if } y^* < 0 \end{Bmatrix}$$

$$P(y_i=1) = \Phi(\alpha_i + \beta M_i + X_i\beta)$$

$$P(y_i=0) = 1-\Phi(\alpha_i + \beta M_i + X_i\beta)$$

, where M is a categorical variable for mover and gentrified neighborhood status (non-mover in gentrified neighborhood, mover within gentrified neighborhood, non-mover in not gentrified neighborhood, and mover within not gentrified neighborhood). The reference category is non-mover in not gentrified neighborhood;

X is a set of individual covariates associated with the outcome and year-fixed effects;

i = index for CHIS respondent.

We then tested the hypothesized relationships in Figure 4.1 among adults who moved to the same neighborhoods (n=2,561) using two main models. The first model (reduced model) predicted likelihood of serious psychological distress in the past year among within-neighborhood movers, using an indicator for living in a low-income and gentrified neighborhood, a set of individual characteristics associated with the outcome, and year fixed-effects. The second model (full model) includes the potential mediator, moved due to unaffordable housing, as an additional independent variable. The probit model specifications for research questions 2 and 3 are:

Reduced model: $y_i^* = \alpha_i + \theta_R T_i + X_i\beta + \varepsilon_i$

$$P(y_i=1) = \Phi(\alpha_i + \theta_R T_i + X_i\beta)$$
$$P(y_i=0) = 1-\Phi(\alpha_i + \theta_R T_i + X_i\beta)$$

Full model: $y_i^* = \alpha_i + \theta_F T_i + \Upsilon Z_i + X_i\beta + \varepsilon_i$

$$P(y_i=1) = \Phi(\alpha_i + \theta_F T_i + \Upsilon Z_i + X_i\beta);$$
$$P(y_i=0) = 1-\Phi(\alpha_i + \theta_F T_i + \Upsilon Z_i + X_i\beta);$$

$$\varepsilon \sim N(0,1)$$
$$y_i = \begin{Bmatrix} 1 \text{ if } y^* > 0 \\ 0 \text{ if } y^* < 0 \end{Bmatrix}$$

, where T is an indicator for living in a low-income and gentrified neighborhood;

Z is an indicator for having moved due to unaffordable housing;

X is a set of individual covariates associated with the outcome and year-fixed effects;

i = index for CHIS respondent.

The estimate for θ_F in the full model represents the direct effect of living and moving within a gentrified neighborhood, relative to living in a not gentrified neighborhood, on likelihood of serious psychological distress (Figure 4.1: path c'). The estimate for Υ is the conditional effect of moving due to unaffordable housing on serious psychological distress (Figure 4.1: path b). We also estimated the effect of living a gentrified neighborhood on having moved due to unaffordable housing, relative to living in a not gentrified neighborhood (Figure 4.1: path a). The total effect of living and moving within a gentrified neighborhood on SPD is captured by θ_R in the reduced model (Figure 4.1: path c), and the difference between θ_R and θ_F is the indirect effect of living in a gentrified neighborhood on SPD, mediated through moving due to unaffordable housing.

Because the latent variable y* is unobserved and the full and reduced models have different scale parameters, we applied the KHB method developed by Breen, Karlson, and Holm (Breen, Karlson, & Holm, 2013) to decompose the full effect of our key independent variable, θ_R, into direct and indirect effects. The KHB method regresses Z on X (path a) and uses the residuals from this regression in the reduced model, which is then assumed to be no more predictive than the full model (Kohler, Karlson, & Holm, 2011). To test whether moving due to unaffordable housing mediates the effect of living in a gentrified neighborhood on SPD, we tested the null hypothesis that the indirect effect equals zero, H_0: $\theta_R - \theta_F = 0$.

Model misspecification and calibration were assessed using the Tukey and Pregibon link test and Hosmer-Lemeshow goodness-of-fit test. Standard errors were adjusted for clustering at the census tract level. All analyses were conducted using Stata 14.

Sensitivity Analyses. Kessler 6 scores (higher scores indicate more distress) may be more sensitive to moving-related stress than the binary variable for SPD, so we repeated all analyses using negative binomial regression and the continuous Kessler 6 score as the outcome. We also limited our sample of movers to residents who moved in the past year, which narrowed the time between exposure (moving residences within the same neighborhood) and the outcome (serious psychological distress or Kessler 6 score). Finally, because age distributions varied across comparison groups, we limited the analytic samples to adults aged 18 to 64.

Results

Research Question 1. Does moving within the same neighborhood increase risk for SPD? If so, is the effect of moving within the same neighborhood on SPD moderated by whether residents lived in gentrified or not gentrified neighborhoods?

Movers. Roughly 28 percent (n=12,463) of adults in Southern California had recently moved to their current addresses no more than five years since their interview date. One-fifth (21%) of recent movers relocated residences to the same neighborhoods. These respondents changed residences but stayed in the neighborhoods they were living in prior to moving. The rates of serious psychological distress among people who moved to different neighborhoods and people who moved to the same neighborhoods were comparable. Approximately 10 percent of all recent movers likely had SPD in the past year. See Table 4.2. The main reasons for moving, however, diverged between movers to different neighborhoods and movers to same neighborhoods. Adults who moved to different neighborhoods were more likely to have moved for work related reasons (10% versus 5%) and because the new neighborhoods were better (e.g., had less crime) (9% versus 6%). Respondents who moved within their neighborhoods more often moved because they couldn't afford their mortgage or rent (14% versus 12%) or due to other housing-related reasons (35% versus 27%). These respondents were also more likely parents (38% versus 31%) and renters (74% versus 68%) compared adults who moved to different neighborhoods, and were less likely to have Bachelor's degrees and health insurance.

Among movers to different neighborhoods, respondents who moved to gentrified neighborhoods were more often Latinx (41% versus 31%), immigrants (42% versus 34%), and renters

(78% versus 68%) than adults who moved to not gentrified neighborhoods. They also were more likely to have low incomes (40% with incomes in the 1st quartile versus 33%), were slightly older in age, less likely to have children in the household (25% versus 32%), and were less likely to feel safe in their neighborhoods most of the time. In contrast, adults who moved to not gentrified neighborhoods were more often non-Hispanic White, younger, educated with higher incomes, homeowners, and more often felt safe in their neighborhoods. Primary reasons for moving were relatively similar between the two groups; a slightly greater fraction of people who moved to gentrified neighborhoods moved for negative housing-related reasons (44% gentrified versus 40% non-gentrified). Eleven percent of movers to gentrified neighborhoods had SPD compared to 10 percent of respondents who moved to not gentrified neighborhoods. It is important to note that the California Health Interview Survey did not ask respondents about the locations of their prior residences, so we do not know whether respondents moved to more resourced neighborhoods or whether upward residential mobility varied between people who moved to gentrified neighborhoods and people who moved to not gentrified neighborhoods. These movers were not included in further analyses.

Among respondents who moved and stayed in their neighborhoods, the sociodemographic characteristics of those living in gentrified and not gentrified communities were noticeably different. Movers within gentrified neighborhoods were more often women (68% gentrified versus 58% not gentrified). Half of movers within gentrified neighborhoods were immigrants, Latinx, and had low incomes compared to roughly a third of movers within not gentrified neighborhoods. Movers within gentrified neighborhoods were also more often renters, slightly more likely to be unemployed, and more likely to report being in fair or poor heath than movers within not gentrified neighborhoods. Although SPD rates (10%) did not differ between the two groups, respondents who moved within gentrified neighborhoods were significantly more likely to move due to negative housing-related reasons (56% gentrified versus 49% not gentrified); 20 percent of respondents who moved within gentrified neighborhoods were unable to afford their mortgages or rents and experienced within-neighborhood displacement, compared to 14 percent of people who moved within not gentrified neighborhoods.

Non-Movers. Non-movers were identified as respondents who 1) lived in the same neighborhoods as within-neighborhood movers and 2) had lived at their current residences for over five years. Nearly 8 percent (n=1,142) of 14,696 non-movers lived in gentrified neighborhoods. Eight percent of non-movers in gentrified neighborhoods had SPD compared to 5 percent of non-movers in not gentrified neighborhoods (Table 4.3). Non-movers in gentrified neighborhoods also had less education and lower incomes, were more likely to be immigrants and uninsured, and more often reported fair or poor health than non-movers in other neighborhoods. Half (51%) of non-movers in gentrified neighborhoods rented their homes compared to 27 percent of non-movers in not gentrified communities.

In-movers, Within-Neighborhood Movers, and Non-Movers in Gentrified Neighborhoods. As mentioned earlier, moves to and within neighborhoods are selective processes, and in gentrified neighborhoods, in-movers or recent residents were more often male (47%) and more likely to have BA/BS degrees (33%) than both within-neighborhood movers and non-movers. Within-neighborhood movers, compared to in-movers and non-movers, were more often female (68%), immigrants (50%), Latinx (50%), and more likely to have children in the household (35%). A vast majority of within-neighborhood movers rented their current homes (87%), compared to 78% of in-movers, and 51% of non-movers. In contrast, non-movers were older in age than in-movers and within-neighborhood movers, were least likely to have children in the household (17%), and least likely to be unemployed (5%). Non-Hispanic White residents represent the largest racial/ethnic group of non-movers in gentrified neighborhoods. Non-movers were also significantly more likely to own their homes and had higher household incomes. Between in-movers and within-neighborhood movers, in-movers to gentrified neighborhoods more often cited have moved to establish their own households, for work-related reasons, and because the neighborhood was better than their previous neighborhoods, whereas within-neighborhood movers were more likely to have moved because they couldn't afford rent or other housing-related reasons. The characteristics and reasons for moving of out-movers are unknown.

Across all three samples, the unadjusted proportion of residents with serious psychological distress was highest among people who moved within the same neighborhoods (10%-12%), followed by non-movers in gentrified neighborhoods (8 to 9%). See Table 4.4. Non-movers in not gentrified neighborhoods had the lowest SPD rate (5% to 8%).

Table 4.5 displays probit regression results for serious psychological distress across three samples. Psuedo-R^2 was approximately .14 for all models, and model specification (link) tests suggested that the probit models were not mis-specified. Respondents who moved within not gentrified neighborhoods were more likely to have serious psychological distress than non-movers in not gentrified neighborhoods, controlling for individual factors in the model. The average marginal effect was 1.3 to 2.7 percentage points. When comparing movers and non-movers in low-income communities, we observed that living and not moving from a gentrified neighborhood increased risk for SPD, relative to living in a low-income and not gentrified neighborhood. The average marginal effect was 1.6 percentage points and statistically significant. The estimated effects of moving within gentrified neighborhoods, relative to not moving in a not gentrified neighborhood, were not statistically significant.

Table 4.6 presents the expected prevalences of SPD if all respondents had low incomes, rented their homes (all other covariates kept at observed values), and were in one of the four comparison groups. Controlling for other individual factors in the models, renters with low incomes who moved within low-income and not gentrified neighborhoods (10% to 13%) had the greatest expected rates of SPD. Non-movers and within-neighborhood movers who had low incomes and rented in gentrified neighborhoods had similar expected rates of SPD. Renters with low incomes who did not move from not gentrified neighborhoods had the lowest expected SPD rates (8% to 10%).

Sensitivity Analyses. We used respondents' Kessler 6 scores as the outcome variable and observed that the results mirrored probit regression results reported in Table 4.4. See Table 4.S1 for details. We also limited our samples to respondents aged 18-64, repeated the probit regression analyses, and observed that while the effects of not moving in gentrified neighborhoods on SPD remained positive, the estimates were no longer statistically significant (Table 4.S2). Finally, we removed cases where respondents' moves occurred long before they were assessed for serious psychological distress and limited the sample size of within-neighborhood movers to those who had moved in the past year. Table 4.5 below summarizes probit and negative binomial regression models in two samples: movers and non-movers residing in low-income neighborhoods aged 18 and over and aged 18-64. Among respondents who had moved in the past year, the estimated effects of moving within a gentrified neighborhood were larger compared to coefficients estimated from the sample of all movers (Table 4.7). Among adults aged 18-64 who moved in the past year, moving within a gentrified neighborhood increased the expected Kessler 6 score 22% (IRR=1.22) relative to not moving in a not gentrified neighborhood. The estimate was statistically significant (p=.03). The estimated effects of moving within not gentrified neighborhoods on SPD and Kessler 6 score, relative to the reference category, were no longer statistically significant when analytic samples were limited to movers who moved in the past year. Non-movers in gentrified neighborhoods, compared to non-movers in not gentrified neighborhoods, on average had increased risk for SPD or greater expected Kessler 6 scores. The estimates were statistically significant across three of the four models.

Research question 2. Does gentrification trigger within-neighborhood displacement, and does displacement affect adult mental health?

In an effort to explore whether living in a gentrified neighborhood, relative to living in a not gentrified neighborhood, contributes to within-neighborhood displacement and impacts movers' mental health, we tested a series of mediation relationships. Table 4.8 presents a summary of estimates for paths a, b, c, and c' illustrated in Figure 4.1. Most estimates were not statistically significant at the .05 level. There was some indication that living in gentrified neighborhoods increased the likelihood that residents moved due to unaffordable housing, relative living in low-income and not gentrified neighborhoods, but estimates were not statistically significant. Within-neighborhood movers who moved because they couldn't afford their rents or mortgages were more likely to have SPD than similar respondents who moved for other reasons. This relationship was not statistically significant among movers in low-income neighborhoods and past-year movers. Moving within in a gentrified neighborhood did not appear to have a direct and statistically significant effect on likelihood of SPD, and KHB results (not shown) were not statistically significant across all samples.

Sensitivity Analyses. In the case that stressors associated with moving were more subtle and unlikely to cause serious psychological distress, we repeated the analyses for paths b, c, and c' using respondents' Kessler 6 scores and negative binomial regression. See Table 4.S3. Moving within the same neighborhood because the rent or mortgage was unaffordable (path b) increased respondents' expected Kessler 6 scores 15%-27%, relative to moving for other reasons. Moving within a low-income and gentrified neighborhood, relative to moving within a not gentrified neighborhood, was not associated with Kessler 6 score (paths c and c').

We also limited our sample of within-neighborhood movers to adults aged 18-64 and repeated all probit and negative binomial regressions. See Table 4.9. Among within-neighborhood movers in this age group, residents of gentrified neighborhoods were more likely than residents of low-income and not gentrified neighborhoods to move due unaffordable housing as opposed to other reasons (path a). Adults who moved to a new residence in the same neighborhood because they couldn't afford housing costs had increased risk for SPD or greater expected Kessler 6 scores than adults who moved for other reasons (path b), and residing in a gentrified neighborhood did not directly increase or decrease risk for SPD or expected Kessler 6 scores compared to living in a gentrified neighborhood (paths c and c'). KHB results (not shown) were not statistically significant across all analyses.

Discussion

This study examined whether living in a gentrified neighborhood, relative to living in a not gentrified neighborhood, increased residents' risks for within-neighborhood displacement and therefore increased their risks for serious psychological distress. We examined these questions through two sets of analyses. The first tested whether moving within the same neighborhood, as opposed to not having recently moved, was associated with likelihood for SPD, and whether the impact of within-neighborhood mobility on SPD was different for residents of gentrified neighborhoods versus residents in not gentrified neighborhoods. Across the four comparison groups, we observed that non-movers in not gentrified neighborhoods had the lowest adjusted rates of SPD. Moving within these neighborhoods had a detrimental effect on mental health and increased the expected proportion of respondents with SPD between 1.3 and 2.7 percentage points. These findings support our hypothesis that moving to the same neighborhood contributes to stress. We also observed that within-neighborhood movers were more often pushed from their prior homes because they couldn't afford the housing payments or because of other housing-related reasons. In contrast, residents who moved to different neighborhoods or in-movers more often moved for work-related reasons or because the new neighborhoods were considered better.

Adjusted rates of SPD for people who moved within gentrified neighborhoods were similar to non-movers in not gentrified neighborhoods across all samples and models. This finding did not change after changing the mental health outcome measure to Kessler 6 scores. Several factors may contribute to these observations. The first is that being able to stay in a gentrified neighborhood counteracted any mental health stress associated with moving. Another explanation is that residents who moved and stayed in gentrified neighborhoods perceived added benefits of living in gentrified neighborhoods and decided that staying in the neighborhood was the best option for them. In both scenarios, advantages of living in a gentrified neighborhood influenced residents' decisions to stay and/or countered the mental health costs of moving. Finally, our study might have been underpowered to detect any impacts moving within gentrified neighborhoods have on mental health stress.

Non-movers in gentrified neighborhoods had increased risk for SPD relative to non-movers in not gentrified neighborhoods. This finding supports results reported in Chapter 3 and suggests that rapid upscaling and changes in the physical, economic, and social characteristics of a community contributes to mental health distress of longtime residents, who, in this study, were defined as residents who had lived in their neighborhoods for over 5 years.

To better understand one of the pathways through which gentrification potentially impacts residents' mental health, we assessed whether living in a gentrified neighborhood elevated risks for within-neighborhood displacement compared to living in a not gentrified neighborhood. We found some support that, controlling for other factors, within-neighborhood movers in gentrified neighborhoods more often moved because they couldn't afford the housing costs compared to within-neighborhood movers in other neighborhoods. Home prices and rental costs climb more rapidly in gentrified neighborhoods, so for existing residents whose incomes did not increase at comparable rates, their housing burdens, the fraction of household income dedicated to housing costs, also increased. We surmised that these residents, confronted with growing financial pressures, had few options but to move to more affordable residences within the same neighborhood. It is possible that housing became unaffordable not because movers' housing costs increased, but because other costs (e.g., education costs, emergency costs, etc.) increased or their incomes decreased. Without panel data and repeated measures of income and employment, we could not discount these alternate explanations, but sudden declines in incomes have not been shown to be more frequent in gentrified neighborhoods than in other low-income neighborhoods. On the contrary, residents who stay in gentrified neighborhoods potentially have greater real income gains than residents who stay in not gentrified neighborhoods (Ellen & O'Regan, 2011).

Primary and sensitivity analyses did suggest that moving to a new residence within the same neighborhood because of unaffordable housing increased respondents' mental health stress relative to moving for other reasons. Living in a gentrified neighborhood, however, did not directly impact mental health outcomes compared to living in a not gentrified neighborhood. Interpreted together, our results suggest that gentrification contributes to within-neighborhood displacement, which then increases the risk for serious psychological distress of movers or displacees. Gentrification did not have a direct effect on the mental health of within-neighborhood movers.

Limitations. Inadequate sample size and insufficient power to detect statistically significant effects was a source of concern. Of the 2,561 CHIS respondents who recently moved to a new residence in the same neighborhood, 235 respondents lived in gentrified neighborhoods. Therefore, our results may be subject to type II error. Sensitivity analyses, although limited to select populations (i.e., adults aged 18-64 and past-year movers) and smaller in sample sizes, did have indications of better model fit than main models, which boosted our confidence in the statistically significant results.

Despite our attempts to compare respondents in low-income neighborhoods, estimates may be affected by unobserved heterogeneity between residents who lived in gentrified neighborhoods and residents whose neighborhoods did not gentrify. This concern especially applies to within-neighborhood movers. Unlike movers within not gentrified neighborhoods, movers within gentrified neighborhoods may have chosen to stay in their neighborhoods because of the changing nature of the neighborhoods and may have had more resources to stay.

The most challenging limitation is the lack of panel data. Our study focused on residents who moved and remained in gentrified neighborhoods. The prior residences of people who recently moved to different neighborhoods were unknown, which limited our abilities to observe all mobility patterns during the study period. Also absent in the study were former residents who moved out of and were potentially displaced from gentrified neighborhoods. As a result, our estimates are subject to sample selection bias. In addition, associations between moving and mental health stress should not be interpreted as causal, because we had one measure of serious psychological stress for each respondent, and therefore could not estimate the marginal effect of moving on mental health distress. Similarly, we did not address potential simultaneity between moving due to housing unaffordability and serious psychological distress but did adjust for other factors that likely mediate the relationship such as employment status and income.

Given data limitations, we were able to observe intra-neighborhood mobility and explore a pathway through which gentrification impacts mental health. We found that gentrification likely induces within-neighborhood displacement, which has a detrimental effect on the mental health of movers. Our results also showed that residents at greatest risk of direct residential displacement, renters with low incomes, had very high predicted SPD rates. On average, as many as 14% of renters aged 18-64 living in low-income neighborhoods with low incomes had serious psychological distress. In addition to adopting anti-displacement policies that help allow residents to remain in their neighborhoods, behavioral health and social support services should be focused on these residents.

Figures and Tables

Figure 4.1. Hypothesized Relationships between Living in a Gentrified Neighborhood, Having Moved due to Unaffordable Housing, and Past Year Serious Psychological Distress among Adults who Recently Moved within the Same Neighborhood

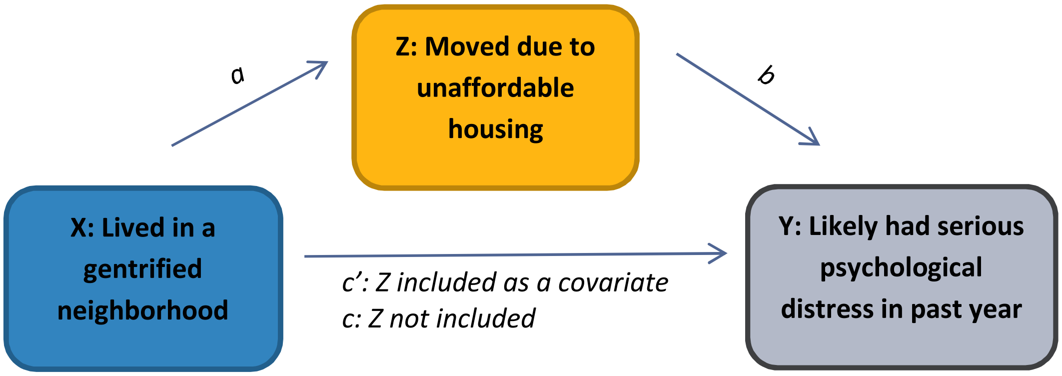


Table 4.1. Respondent Categories by Mover Status and Gentrified Status of Neighborhood – n=17,257

	Neighborhood is gentrified	**Neighborhood is not gentrified**
Moved in the past 5 years to the same neighborhood	Mover within gentrified neighborhood (n=235)	Mover within not gentrified neighborhood (n=2,326)
Lived in the same neighborhood as a mover & did not move in past 5 years	Non-mover within gentrified neighborhood (n=1,142)	Non-mover within not gentrified neighborhood - ***Reference group*** (n=13,554)

Figure 4.2. Variables Used to Identify Movers and Non-Movers, Within-Neighborhood Movers, and Moving Due to Unaffordable Housing, California Health Interview Survey (2011-2015)

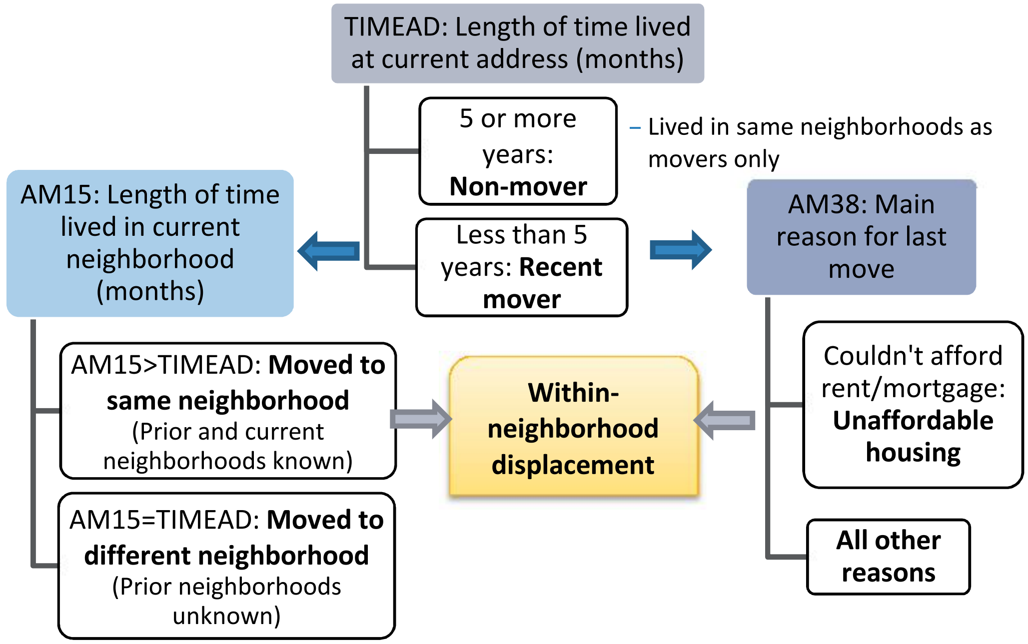


Table 4.2. Serious Psychological Distress, Sociodemographic Characteristics, and Reasons for Moving Among Movers, by Gentrified Status of Neighborhood, Adults Aged 18 and Over

	Movers: Lived at current residence fewer than five years					
	Moved to different neighborhood[a] (n=9,902)	Moved to same neighborhood (n=2,561)	Moved to Not Gentrified[a] (n=9,107)	Moved to Gentrified[a] (n=795)	Moved within Not Gentrified (n=2,326)	Moved within Gentrified (n=235)
Likely had serious psychological distress in the past year	9.8	9.92	9.7	10.7	9.9	10.2
Reasons for Moving						
Change in marital/relationship status	6.3	7.6	6.4	6.2	7.9	5.1
To establish own household	10.8	9.2	10.7	10.8	9.4	6.8
For child's education/to attend or leave	1.6	1.1	1.7	0.8	1.1	--
To attend or leave college	2.5	2.1	2.5	2.5	2.2	--
Work related	10.1	4.9	10.4	7.0	5.0	3.8
Couldn't afford mortgage/rent	12.1	14.1	12.0	13.6	13.5	20.0
Other housing related	26.8	35.0	26.6	29.1	34.8	36.6
Better neighborhood/less crime	8.8	5.9	8.8	8.8	6.1	4.7
Closer to family or family-related reason	1.9	0.4	1.9	1.6	0.4	0.0
Changes in renting/lease	1.2	0.5	1.2	1.1	0.6	0.0
Other	17.9	19.3	17.8	18.5	19.1	20.9
Moved for Negative Housing-Related Reasons[b]	40.3	49.6	40.0	43.9	48.9	56.6
Gender						
Female	56.3	58.7	56.5	53.5	57.8	67.7
Male	43.7	41.3	43.5	46.5	42.2	32.3
Age Category						
18-25	14.1	14.5	14.1	14.3	14.3	16.2

	Movers: Lived at current residence fewer than five years					
	Moved to different neighborhood[a] (n=9,902)	Moved to same neighborhood (n=2,561)	Moved to Not Gentrified[a] (n=9,107)	Moved to Gentrified[a] (n=795)	Moved within Not Gentrified (n=2,326)	Moved within Gentrified (n=235)
26-45	37.9	37.5	38.0	37.4	37.6	36.6
46-64	29.4	32.3	29.8	25.5	32.4	31.5
65+	18.5	15.7	18.2	22.8	15.7	15.7
Nativity						
Born outside US	34.7	36.8	34.1	41.6	35.5	50.2
Born in US	65.3	63.2	65.9	58.4	64.5	49.8
English Proficiency						
Speaks only English or speaks English well	83.3	82.2	84.0	75.1	83.3	71.5
Speaks English not well or not at all	16.7	17.8	16.0	24.9	16.7	28.5
Race/ethnicity						
Latinx	32.2	39.0	31.4	41.4	37.8	51.5
NH White	43.3	40.3	44.0	34.3	41.8	26.4
NH Black	8.3	8.2	8.3	8.7	8.3	7.7
Asian, AIAN, NHPI, Two or More Race	16.2	12.4	16.3	15.6	12.2	14.5
Has Bachelor's degree or higher	37.0	31.8	37.4	32.7	32.8	21.7
Household Income						
1st quartile	33.2	36.2	32.6	39.9	34.8	49.8
2nd and 3rd quartile	48.1	48.2	48.2	47.0	49.1	39.2
4th quartile	18.7	15.6	19.2	13.1	16.1	11.1
Homeownership Status						
Rent or other arrangement	68.3	73.8	67.5	77.6	72.5	86.8
Own home	31.7	26.2	32.5	22.4	27.5	13.2
Employment Status						

	Movers: Lived at current residence fewer than five years					
	Moved to different neighborhood[a] (n=9,902)	Moved to same neighborhood (n=2,561)	Moved to Not Gentrified[a] (n=9,107)	Moved to Gentrified[a] (n=795)	Moved within Not Gentrified (n=2,326)	Moved within Gentrified (n=235)
Employed or not looking	92.0	90.4	92.1	91.2	90.6	88.1
Unemployed	8.0	9.6	7.9	8.8	9.4	11.9
Insurance Status						
Currently uninsured or uninsured any time	23.3	27.2	23.2	24.8	26.6	33.2
Insured all year	76.7	72.8	76.8	75.2	73.4	66.8
Marital Status						
Married/living with partner	49.2	47.9	49.7	43.1	48.3	43.8
Widowed/separated/divorced	24.8	27.3	24.5	27.9	27.1	29.4
Never married	26.0	24.8	25.8	28.9	24.6	26.8
Reported fair or poor health	23.6	23.5	23.2	27.7	23.1	27.2
Chronic Conditions						
No reported conditions	72.6	74.0	72.9	70.1	73.9	75.3
Asthma, diabetes, &/or heart disease	27.4	26.0	27.1	29.9	26.1	24.7
Current smoker	14.5	16.2	14.5	15.5	16.3	15.3
Social Capita Score						
Mean (SD)	5.86 (1.21)	5.79 (1.26)	5.87 (1.21)	5.67 (1.25)	5.81 (1.25)	5.59 (1.32)
Feels safe in the neighborhood all or most of the time	85.3	83.8	85.7	80.8	84.6	75.7
Children in household	31.0	37.5	31.5	25.2	37.7	34.9
Year						
2011	19.9	31.3	20.0	19.5	30.7	36.6
2012	18.5	31.1	18.5	19.0	30.3	38.7
2013	18.3	25.6	18.5	15.7	26.4	17.9

	Movers: Lived at current residence fewer than five years					
	Moved to different neighborhood[a] (n=9,902)	Moved to same neighborhood (n=2,561)	Moved to Not Gentrified[a] (n=9,107)	Moved to Gentrified[a] (n=795)	Moved within Not Gentrified (n=2,326)	Moved within Gentrified (n=235)
2014	16.8	4.7	16.6	18.4	4.9	2.1
2015	26.5	7.3	26.4	27.4	7.6	4.7

Sources: California Health Interview Survey 2011, 2012, 2013, 2014, 2015; American Community Survey 2006-2010 and 2011-2015; Home Mortgage Disclosure Act Aggregate Data 2010 and 2015

[a] Not included in regression analyses.

[b] Negative housing-related reasons include inability to afford rent or mortgage and other housing reasons.

Table 4.3. Serious Psychological Distress and Sociodemographic Characteristics of Non-movers by Gentrified Status of Neighborhood, Adults Aged 18 and Over

	Non-Movers: Lived in same neighborhood as R who moved to same neighborhood & at current residence for more than five years	
	Non-Mover in Not Gentrified (n=13,554)	Non-Mover in Gentrified (n=1,142)
Likely had serious psychological distress in the past year	5.4	8.2
Gender		
Female	59.6	60.3
Male	40.4	39.7
Age Category		
18-25	5.5	7.4
26-45	14.0	17.4
46-64	38.6	32.0
65+	41.9	43.3
Nativity		
Born outside US	27.6	39.3
Born in US	72.4	60.7
English Proficiency		
Speaks only English or speaks English well	87.7	77.6
Speaks English not well or not at all	12.3	22.4
Race/ethnicity		
Latinx	22.5	34.2
NH White	59.1	43.3
NH Black	5.9	7.6
Asian, AIAN, NHPI, Two or More Race	12.6	14.9
Has Bachelor's degree or higher	42.1	30.5
Household Income		
1st quartile	20.5	37.6
2nd and 3rd quartile	51.6	48.1
4th quartile	28.0	14.4
Homeownership Status		
Rent or other arrangement	26.9	50.6
Own home	73.1	49.4
Employment Status		
Employed or not looking	95.7	94.8
Unemployed	4.3	5.2
Insurance Status		

	Non-Movers: Lived in same neighborhood as R who moved to same neighborhood & at current residence for more than five years	
	Non-Mover in Not Gentrified (n=13,554)	Non-Mover in Gentrified (n=1,142)
Currently uninsured or uninsured any time	11.2	15.9
Insured all year	88.8	84.2
Marital Status		
Married/living with partner	53.6	40.1
Widowed/separated/divorced	29.4	35.2
Never married	17.0	24.7
Reported fair or poor health	21.8	29.6
Chronic Conditions		
No reported conditions	68.2	64.2
Asthma, diabetes, &/or heart disease	31.8	35.8
Current smoker	8.7	9.9
Social Capita Score		
Mean (SD)	6.14 (1.16)	5.84 (1.19)
Feels safe in the neighborhood all or most of the time	91.9	84.8
Children in household	18.6	16.5
Year		
2011	21.2	18.3
2012	23.1	23.7
2013	21.8	21.5
2014	17.2	18.0
2015	16.8	18.5

Sources: California Health Interview Survey 2011, 2012, 2013, 2014, 2015; American Community Survey 2006-2010 and 2011-2015; Home Mortgage Disclosure Act Aggregate Data 2010 and 2015

[a] Not included in regression analyses.

[b] Negative housing-related reasons include inability to afford rent or mortgage and other housing reasons.

Table 4.4. Proportion of Residents with Serious Psychological Distress by Moving Status and Gentrified Status of Neighborhood, Adults Aged 18 and Over

Sample	Non-Mover in Gentrified	Mover within Gentrified	Non-Mover in Not Gentrified	Mover within Not Gentrified
Within-neighborhood movers & non-movers living in the same neighborhoods (n=17,257)	8.2%	10.2%	5.4%	9.9%
Within-neighborhood movers & non-movers in low-income neighborhoods[a] (n=8,823)	8.4%	10.2%	7.5%	12.2%
Within-neighborhood movers & non-movers in same, low-income neighborhoods (n=5,218)	8.3%	10.2%	7.0%	12.2%

Sources: California Health Interview Survey 2011, 2012, 2013, 2014, 2015; American Community Survey 2006-2010 and 2011-2015; Home Mortgage Disclosure Act Aggregate Data 2010 and 2015

[a] Low-income neighborhoods had median household incomes that were less than 80% of the median incomes for their respective counties.

Table 4.5. Probit Regression Results[a] for Past Year Serious Psychological Distress, Within-Neighborhood Movers and Non-Movers in Southern California Neighborhoods, Adults Aged 18 and Over

	Within-neighborhood movers & non-movers living in the same neighborhoods (n=17,257)		Within-neighborhood movers & non-movers in low-income neighborhoods (n=8,823)		Within-neighborhood movers & non-movers in same, low-income neighborhoods (n=5,218)	
Mover and Gentrification Status - ref: Non-mover in not gentrified	**b (SE)**	**AME**	**b (SE)**	**AME**	**b (SE)**	**AME**
Non-Mover in Gentrified	0.09 (0.066)	0.01	0.116** (0.052)	.016**	0.131* (0.073)	0.017*
Mover within Gentrified	0.021 (0.112)	0.002	0.081 (0.112)	0.011	0.14 (0.118)	0.018
Mover within Not Gentrified	0.119** (0.048)	.013**	0.132* (0.073)	.018*	0.201** (0.081)	0.027**

Sources: California Health Interview Survey 2011, 2012, 2013, 2014, 2015; American Community Survey 2006-2010 and 2011-2015; Home Mortgage Disclosure Act Aggregate Data 2010 and 2015

[a] Coefficients and average marginal effects (AMEs). Covariates in probit models included respondent age, gender, race/ethnicity, marital status, education, income, homeownership status, insurance status, English proficiency, overall health, chronic conditions, smoking status, perceived safety in the neighborhood, presence of children, social capita score, and year fixed-effects. Robust standard errors were estimated to adjust for clustering in census tracts.

** p<.05; * p<.10

Table 4.6. Expected Prevalence[a] of Serious Psychological Distress among Residents Who Rented Their Homes and Had Low Incomes[b] by Moving Status and Gentrified Status of Neighborhood, Adults Aged 18 and Over

Sample	Non-Mover in Gentrified	Mover within Gentrified	Non-Mover in Not Gentrified	Mover within Not Gentrified
Within-neighborhood movers & non-movers living in the same neighborhoods (n=17,257)	9.0%	8.1%	7.8%	9.5%
Within-neighborhood movers & non-movers in low-income neighborhoods (n=8,823)	11.7%	11.1%	9.8%	12%
Within-neighborhood movers & non-movers in same, low-income neighborhoods (n=5,218)	11.4%	11.5%	9.3%	12.6%

Sources: California Health Interview Survey 2011, 2012, 2013, 2014, 2015; American Community Survey 2006-2010 and 2011-2015; Home Mortgage Disclosure Act Aggregate Data 2010 and 2015

[a] Expected prevalences represent predictive margins calculated from probit models. Covariates in these models included respondent age, gender, race/ethnicity, marital status, education, income, homeownership status, insurance status, English proficiency, overall health, chronic conditions, smoking status, perceived safety in the neighborhood, presence of children, social capita score, and year fixed-effects. Robust standard errors were estimated to adjust for clustering in census tracts.

[b] Residents with low incomes had income-to-poverty threshold ratios that were in the first quartile of a sample of all respondents (less than 144% of the federal poverty level).

Table 4.7. Probit and Negative Binomial Regression Results[a], Within-Neighborhood Movers Who Moved in the Past Year and Non-Movers in Low-Income Southern California Neighborhoods, Adults Aged 18+ and 18-64

	Aged 18 and Over		Aged 18-64	
	Within-neighborhood movers who moved in the past year & non-movers in low-income neighborhoods (n=8,535)		Within-neighborhood movers who moved in the past year & non-movers low-income neighborhoods (n=5,328)	
Mover and Gentrification Status - ref: Non-mover in not gentrified	**Probit b (SE)**	**Negative Binomial IRR[b] (SE)**	**Probit b (SE)**	**Negative Binomial IRR[b] (SE)**
Non-Mover in Gentrified	0.117** (0.052)	1.08** (0.029)	0.083 (0.063)	1.071** (0.036)
Mover within Gentrified	0.14 (0.167)	1.162* (0.099)	0.185 (0.173)	1.215** (0.11)
Mover within Not Gentrified	0.056 (0.102)	1.058 (0.061)	0.054 (0.109)	1.062 (0.065)

Sources: California Health Interview Survey 2011, 2012, 2013, 2014, 2015; American Community Survey 2006-2010 and 2011-2015; Home Mortgage Disclosure Act Aggregate Data 2010 and 2015

[a] The outcome for the probit models was an indicator for serious psychological distress. The outcome for the negative binomial models was the respondent's Kessler 6 score. Covariates in all models included respondent age, gender, race/ethnicity, marital status, education, income, homeownership status, insurance status, English proficiency, overall health, chronic conditions, smoking status, perceived safety in the neighborhood, presence of children, social capita score, and year fixed-effects. Robust standard errors were estimated to adjust for clustering in census tracts.

[b] IRR represents e^b and may be interpreted as the factor change in the expected Kessler 6 score for the group of interest as compared to the reference group.

** p<.05; * p<.10

Table 4.8. Mediation Pathway Models[a] for Serious Psychological Distress, Within-Neighborhood Movers in Southern California Neighborhoods, Adults Aged 18 and Over

	All Within-Neighborhood Movers (n=2,561)	All Within-Neighborhood Movers in Low-Income Neighborhoods (n=972)	Within-Neighborhood Movers who Moved in Past Year (n=1,162)
Path a: Are adults who moved within gentrified neighborhoods more likely to move due to unaffordable housing than similar adults who moved in not gentrified neighborhoods? ***Outcome: Unaffordable housing***			
Gentrification Status - ref: Neighborhood not gentrified			
Neighborhood gentrified	.120 (.11)	.188 (.122)	.076 (.152)
Path b: Does moving due to unaffordable housing, relative to moving for other reasons, impact respondents' likelihood for serious psychological distress? ***Outcome: Had serious psychological distress***			
Main Reason for Move - ref: Other reasons			
Unaffordable housing	.182* (.097)	.056 (.143)	.199 (.148)
Path c: Among adults who recently moved within the same neighborhood, does living in a gentrified neighborhood increase likelihood of serious psychological distress compared to living in a not gentrified neighborhood? ***Outcome: Had serious psychological distress***			
Gentrification Status - ref: Neighborhood not gentrified			
Neighborhood gentrified	-.071 (.117)	-.139 (.127)	-.044 (.176)
Path c': Does moving to another residence within the neighborhood due to unaffordable housing mediate the relationship between gentrification and mental health? ***Outcome: Had serious psychological distress***			
Gentrification Status - ref: Neighborhood not gentrified			
Neighborhood gentrified	-.083 (.119)	-.146 (.128)	-.052 (.179)
Main Reason for Move - ref: Other reasons			
Unaffordable housing	.185* (.097)	.070 (.144)	.201 (.148)

Sources: California Health Interview Survey 2011, 2012, 2013, 2014, 2015; American Community Survey 2006-2010 and 2011-2015; Home Mortgage Disclosure Act Aggregate Data 2010 and 2015

[a] All models were probit models. Covariates for all models included respondent age, gender, race/ethnicity, marital status, education, income, homeownership status, insurance status, English proficiency, overall health, chronic conditions, smoking status, perceived safety in the neighborhood, presence of children, social capita score, and year fixed-effects. Robust standard errors were estimated to adjust for clustering in census tracts.

** p<.05; * p<.10

Table 4.9. Mediation Pathway Models[a] for Serious Psychological Distress or Kessler 6 Score, Within-Neighborhood Movers in Southern California Neighborhoods, Adults Aged 18-64

	All Within-Neighborhood Movers (n=2,158)		All Within-Neighborhood Movers in Low-Income Neighborhoods (n=829)		Within-Neighborhood Movers who Moved in Past Year (n=994)	
Path a: Are adults who moved within gentrified neighborhoods more likely to move due to unaffordable housing than similar adults who moved in not gentrified neighborhoods? *Outcome: Unaffordable housing*						
	b (SE)	**IRR[b] (SE)**	**b (SE)**	**IRR[b] (SE)**	**b (SE)**	**IRR[b] (SE)**
Gentrification Status - ref: Neighborhood not gentrified						
Neighborhood gentrified	.181 (.117)	NA	.242* (.13)	NA	.097 (.166)	NA
Path b: Does moving for negative housing-related reasons, relative to moving for other reasons, impact respondents' likelihood for serious psychological distress? *Outcome: Had serious psychological distress or Kessler 6 score*						
Main Reason for Move - ref: Other reasons						
Unaffordable housing	.239** (.101)	1.269** (.068)	.093 (.149)	1.148* (.088)	.213 (.153)	1.27** (.103)
Path c: Among adults who recently moved within the same neighborhood, does living in a gentrified neighborhood increase likelihood of serious psychological distress compared to living in a not gentrified neighborhood? *Outcome: Had serious psychological distress or Kessler 6 score*						
Gentrification Status - ref: Neighborhood not gentrified						
Neighborhood gentrified	-.047 (.121)	0.935 (.069)	-.11 (.131)	.946 (.077)	-.014 (.181)	1.03 (.098)
Path c': Does moving to another residence within the neighborhood due to unaffordable housing mediate the relationship between gentrification and mental health? *Outcome: Had serious psychological distress or Kessler 6 score*						
Gentrification Status - ref: Neighborhood not gentrified						
Neighborhood gentrified	-.066 (.124)	.920 (.068)	-.121 (.132)	.934 (.076)	-.023 (.184)	1.027 (.099)
Main Reason for Move - ref: Other reasons						
Unaffordable housing	.242** (.101)	1.274** (.068)	.105 (.15)	1.156* (.089)	.214 (.154)	1.27** (.103)

Sources: California Health Interview Survey 2011, 2012, 2013, 2014, 2015; American Community Survey 2006-2010 and 2011-2015; Home Mortgage Disclosure Act Aggregate Data 2010 and 2015

[a] The model for path a was a probit model. Models for paths b, c, and c' were probit and negative binomial models. Covariates for all models included respondent age, gender, race/ethnicity, marital status, education, income, homeownership status, insurance status, English proficiency, overall health, chronic conditions, smoking status, perceived safety in the neighborhood, presence of children, social

capita score, and year fixed-effects. Robust standard errors were estimated to adjust for clustering in census tracts.

[b] IRR represents e^b and may be interpreted as the factor change in the expected Kessler 6 score for the group of interest as compared to the reference group.

** p<.05; * p<.10

Supplemental Materials

Table 4.S1. Negative Binomial Regression Results[a] for Kessler 6 Score, Within-Neighborhood Movers and Non-Movers in Southern California Neighborhoods, Adults Aged 18 and Over

	Within-neighborhood movers & non-movers living in the same neighborhoods (n=17,257)		Within-neighborhood movers & non-movers in low-income neighborhoods (n=8,823)		Within-neighborhood movers & non-movers in same, low-income neighborhoods (n=5,218)	
Mover and Gentrification Status - ref: Non-mover in not gentrified	**IRR[b] (SE)**	**AME**	**IRR (SE)**	**AME**	**IRR (SE)**	**AME**
Non-Mover in Gentrified	1.055* (0.034)	0.203	1.077** (0.029)	0.324**	1.07* (0.039)	0.294*
Mover within Gentrified	.968 (0.069)	-0.12	1.049 (0.075)	0.204	1.08 (0.079)	0.334
Mover within Not Gentrified	1.11** (0.029)	0.41**	1.085** (0.045)	0.358*	1.119** (0.049)	.496**

Sources: California Health Interview Survey 2011, 2012, 2013, 2014, 2015; American Community Survey 2006-2010 and 2011-2015; Home Mortgage Disclosure Act Aggregate Data 2010 and 2015

[a] Covariates in negative binomial models included respondent age, gender, race/ethnicity, marital status, education, income, homeownership status, insurance status, English proficiency, overall health, chronic conditions, smoking status, perceived safety in the neighborhood, presence of children, social capita score, and year fixed-effects. Robust standard errors were estimated to adjust for clustering in census tracts.

[b] IRR represents e^b and may be interpreted as the factor change in the expected Kessler 6 score for the group of interest as compared to the reference group.

** p<.05; * p<.10

Table 4.S2. Probit Regression Results[a] for Past Year Serious Psychological Distress, Within-Neighborhood Movers and Non-Movers in Southern California Neighborhoods, Adults Aged 18-64

	Within-neighborhood movers & non-movers living in the same neighborhoods (n=10,682)		Within-neighborhood movers & non-movers in low-income neighborhoods (n=5,622)		Within-neighborhood movers & non-movers in same, low-income neighborhoods (n=3,361)	
Mover and Gentrification Status - ref: Non-mover in not gentrified	**b (SE)**	**AME**	**b (SE)**	**AME**	**b (SE)**	**AME**
Non-Mover in Gentrified	0.05 (0.081)	0.006	0.081 (0.062)	0.013	0.103 (0.089)	0.015
Mover within Gentrified	0.084 (0.118)	0.011	0.106 (0.118)	0.017	0.19 (0.127)	0.029
Mover within Not Gentrified	0.137** (0.052)	.019**	0.125 (0.080)	0.02	0.217** (0.092)	.034**

Sources: California Health Interview Survey 2011, 2012, 2013, 2014, 2015; American Community Survey 2006-2010 and 2011-2015; Home Mortgage Disclosure Act Aggregate Data 2010 and 2015

[a] Covariates in negative binomial models included respondent age, gender, race/ethnicity, marital status, education, income, homeownership status, insurance status, English proficiency, overall health, chronic conditions, smoking status, perceived safety in the neighborhood, presence of children, social capita score, and year fixed-effects. Robust standard errors were estimated to adjust for clustering in census tracts.

** p<.05; * p<.10

Table 4.S3. Mediation Pathway Models[a] for Kessler 6 Score, Within-Neighborhood Movers in Southern California Neighborhoods, Adults Aged 18 and Over

	All Within-Neighborhood Movers (n=2,561)	All Within-Neighborhood Movers in Low-Income Neighborhoods (n=972)	Within-Neighborhood Movers who Moved in Past Year (n=1,162)
Path a: Are adults who moved within gentrified neighborhoods more likely to move due to unaffordable housing than similar adults who moved in not gentrified neighborhoods? ***Outcome: Unaffordable housing***			
	b (SE)	b (SE)	b (SE)
Gentrification Status - ref: Neighborhood not gentrified			
Neighborhood gentrified	.120 (.11)	.188 (.122)	.076 (.152)
Path b: Does moving due to unaffordable housing, relative to moving for other reasons, impact respondents' likelihood for serious psychological distress? ***Outcome: Kessler 6 Score***			
	IRR[b] (SE)	IRR (SE)	IRR (SE)
Main Reason for Move - ref: Other reasons			
Unaffordable housing	1.23** (.064)	1.144** (.082)	1.275** (.099)
Path c: Among adults who recently moved within the same neighborhood, does living in a gentrified neighborhood increase likelihood of serious psychological distress compared to living in a not gentrified neighborhood? ***Outcome: Kessler 6 Score***			
Gentrification Status - ref: Neighborhood not gentrified			
Neighborhood gentrified	.903 (.064)	.914 (.071)	.987 (.087)
Path c': Does moving to another residence within the neighborhood due to unaffordable housing mediate the relationship between gentrification and mental health? ***Outcome: Had serious psychological distress***			
Gentrification Status - ref: Neighborhood not gentrified			
Neighborhood gentrified	.893 (.063)	.905 (.071)	.985 (.087)
Main Reason for Move - ref: Other reasons			
Unaffordable housing	1.234** (.064)	1.153** (.083)	1.275** (.099)

Sources: California Health Interview Survey 2011, 2012, 2013, 2014, 2015; American Community Survey 2006-2010 and 2011-2015; Home Mortgage Disclosure Act Aggregate Data 2010 and 2015

[a] The model for path a was a probit model. Models for paths b, c, and c' were negative binomial models. Covariates for all models included respondent age, gender, race/ethnicity, marital status, education, income, homeownership status, insurance status, English proficiency, overall health, chronic conditions, smoking status, perceived safety in the neighborhood, presence of children, social capita score, and year fixed-effects. Robust standard errors were estimated to adjust for clustering in census tracts.

[b] IRR represents e^b and may be interpreted as the factor change in the expected Kessler 6 score for the group of interest as compared to the reference group.

** $p<.05$; * $p<.10$

Conclusions, Policy Implications, and Future Research

Summary of Results

This dissertation advances knowledge on gentrification and its impact on the mental health of adult residents. We began by applying three strategies for measuring neighborhood upscaling and identifying neighborhoods that gentrified between 2010 and 2015. We observed that the three strategies generated disparate sets of gentrified census tracts, which had notable implications on assessing the relationship between gentrification and mental health. Although not conflicting, observed associations between living in a gentrified neighborhood and risk for serious psychological distress did not coincide. These results emphasize the importance of the strategy used to identify gentrified neighborhoods, especially when evaluating the effects of gentrification on individual outcomes. Overall, we observed support for including shifts in the socioeconomic characteristics of residents (e.g., education, household income, proportion of middle- to high-income residents), changes in median rents, and, based on sensitivity analyses in Chapter 3, racial/ethnic transitions (e.g., changes in the proportion of non-Hispanic White residents) as indicators of gentrification.

Adults living in gentrified neighborhoods had increased risk for serious psychological distress compared to similar adults in low-income and not gentrified neighborhoods. This effect was only observed among long-term residents, renters, and residents with low incomes, which indicates that gentrification causes distress by intensifying financial pressures, and that residents with the least financial protections—adults with low incomes and renters—are disproportionately impacted. Upscaling in both low-income and middle- to high-income neighborhoods also elevated risk for serious psychological distress among long-term residents (as well as renters and residents with low incomes) and suggests that despite the benefits that upscaling potentially offers to residents, rapid changes to the neighborhood can feel disconcerting for longtime residents and generate stress.

Our findings were robust against efforts to address residential selection, and current residents of gentrified neighborhoods appeared to have experienced substantial neighborhood change and therefore were exposed to the consequences of gentrification. Results from instrumental variables estimation does not support the concern that estimates were influenced by endogeneity arising from reverse causality. We also cannot conclude that the key independent variable is exogenous, but feel optimistic to have identified two instruments for gentrification that were not directly associated with mental health distress: 1) distance between a neighborhood and the nearest high-income neighborhood and 2) the cross-level interaction between whether children are present in a household and the difference in mean school rank relative to similar schools. In cases where panel data are limited, instrumental variables estimation with the right instruments is a powerful technique for establishing causal inference.

In Chapter 4, we saw that moving was associated with greater risk for mental health stress, and that non-movers in gentrified neighborhoods had elevated risks for serious psychological distress compared to non-movers in not gentrified neighborhoods. Expected rates of serious psychological distress among renters with low-incomes—residents at greatest risk for direct residential displacement—were as high as 13 percent. We also identified within-neighborhood movers in the dataset and found some support that residents in gentrified neighborhoods were more likely to experience within-neighborhood displacement, or moving to a different residential unit within the same neighborhood because the previous home was unaffordable, compared to residents in not gentrified neighborhoods. This finding is consistent with observations in prior studies that gentrification raises housing burden for some residents, namely renters, and exerts added pressures to combine households, move to more affordable units within the neighborhood, or to find affordable units outside of the neighborhood. Moving due to unaffordable housing was positively associated with mental health distress. With issues related to sample selection and reverse causality in mind, these findings suggest that gentrification increases residents' likelihood of experiencing within-neighborhood displacement, which then elevates mental health stress.

Policy Implications

This dissertation offers evidence that gentrification, often described as a neighborhood transition process that creates "winners and losers," has a mental health cost on current residents, and that longtime residents, renters, and people with low incomes carry much of the burden (Grant, 2003; Mellnik, Cameron, Lu, Badger, & Downs, 2016). The author of this dissertation prefers to describe longtime residents of gentrified neighborhoods, renters, and people with low incomes as residents who are being left behind, while others potentially benefit from neighborhood upscaling. This has implications for population health and health inequities. By elevating levels of mental health distress of population groups who are already disproportionately exposed to stressors such as discrimination and threats to financial security and safety, gentrification can exacerbate mental health inequities (American Psychological Association, 2017; Safran et al., 2009).

Community members have organized to resist gentrification and investment that does not benefit current residents (King & Lowe, 2018; Kwak Nancy, 2018). Scholars have pointed out the roles strong social ties and shared ethnic identity can have in harnessing community power to challenge and transform investments (Balzarini & Shlay, 2017; Sandoval, 2018). Cities and municipalities have examined and adopted anti-displacement policies to create new affordable housing units, preserve existing affordable housing, protect existing tenants, and that build the assets of residents with low incomes (Crispell et al., 2017). Such policies include rent control ordinances and Just Cause eviction ordinances, which act to limit reasons tenants may be evicted and help stem the reproduction of urban poverty (Desmond, 2012). In Los Angeles County, the most common anti-displacement policies were those that aim to preserve affordable housing, but as much as 40% of jurisdictions in the county did not have one anti-displacement policy in place in 2018 (Gonzalez, Ong, Loukaitou-Sideris, Pascual, & Graziani, 2018).[3] Finally, local leaders in 10 cities have also created the All-In Cities Anti-Displacement Policy Network to put policies and systems in place to reduce displacement and increase long-term affordable housing for residents at greatest risk of displacement. Lessons learned from these efforts will be critical for curbing residential, cultural, and commercial displacement and for increasing the housing security of marginalized communities and people with low incomes.

Future Research

A key challenge encountered in this dissertation were limitations associated with using cross-sectional data. We took care in designing our studies and applied econometric approaches where appropriate to reduce potential validity biases, and we found some consistent evidence that gentrification has a negative impact on the mental health of current residents. Absent in this study were out-movers or the people who recently moved out of or were displaced from their communities. We can surmise that given that within-neighborhood displacement is more common in gentrified neighborhoods and can increase mental health distress, and if we assume that within-neighborhood movers have more social and financial resources than out-movers, out-movers from gentrified neighborhoods are worse off than those who left not gentrified neighborhoods. Outcomes likely depend on whether residents previously owned their homes. But without panel data, we could not test this hypothesis or compare the mental health statuses of out-movers. We were also unable to observe transitions from being housed to homelessness.

Longitudinal studies are needed to fill knowledge gaps on links between gentrification, gentrification-induced displacement, and mental health. One research opportunity is the Opportunity Zones created by the Tax Cuts and Jobs Act of 2017. Opportunity Zones are economically-distressed

[3] The Urban Displacement Project is in the process of evaluating the effectiveness of anti-displacement policies in stabilizing communities.

communities where new investments may be eligible for preferential tax treatment. By tracking and documenting the characteristics, movement, and mental health outcomes of residents in these communities prior to investment and over the years, researchers can gain deeper understanding of the relationships between investment, gentrification, and changes in residents' mental health. Finally, we cannot ignore the value of qualitative research and its role in not only fortifying quantitative measures of gentrification with the lived experiences of residents, but also in uncovering how gentrification affects health.

Displacement is one of the pathways through which gentrification can impact mental health; sensitivity analysis results demonstrated that while some dimensions of neighborhood change (e.g., shifts in the proportion of residents with higher incomes and college degrees) increase risk for mental health distress, other shifts in the neighborhood (e.g., increase in the proportion of non-Hispanic White residents) may improve mental health. The finding that increased proportions of non-Hispanic White residents potentially improves mental health raises questions about the role of race or ethnicity in gentrification processes and how gentrification impacts racial/ethnic groups. Extant studies in this area have focused on the race/ethnicity of gentrifiers and less so on non-gentrifiers (Huse, 2018). Although initial analyses did not imply that the impact of gentrification on mental health differs between people of color and non-Hispanic Whites, future studies should focus on the mental health consequences of gentrification on racial/ethnic minorities, the role of ethnic enclaves, and of being part of the dominant group in a neighborhood. Finally, sensitivity analysis results also set the groundwork for exploring the ecologic effects of gentrification on the mental health of communities and neighboring communities. Spatial econometric models will have an important function in future studies.

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