THE EFFECT OF GENTRIFICATION AND DISPLACEMENT ON POPULATION HEALTH BEHAVIOR AND OUTCOMES

A THESIS

Presented to

The Faculty of the Department of Economics and Business

The Colorado College

In Partial Fulfillment of the Requirements for the BESoc Degree

Bachelor of Arts

By:

Greg Phillips

May 2025

THE EFFECT OF GENTRIFICATION AND DISPLACEMENT ON POPULATION HEALTH BEHAVIOR AND OUTCOMES

Greg Phillips

May 2025

Business, Economics, and Society

Abstract

Gentrification has gained significant attention focused on its effects on health behaviors / risks and health outcomes. Using census tract level demographic data and health data, this study examines the relationship between gentrification and health and how race interacts with gentrification status in this relationship. I find that gentrification status is associated with more positive health outcomes in the absence of minority residents. This relationship is stronger in more intensely gentrifying tracts. However, I find that as the percent of minority residents living in a gentrifying tract increases this relationship flips. Increasing the percent of minority residents living in a gentrifying tract is associated with more negative health outcomes. This relationship is also stronger in more intensely gentrifying tracts. These findings shed new light on the relationship between gentrification and health and how the distribution of health outcomes perpetuates issues of health inequity.

KEYWORDS: (Gentrification, Displacement, Race, Health)

JEL CODES: (I14, I15, I12)

ON MY HONOR, I HAVE NEITHER GIVEN NOR RECEIVED
UNAUTHORIZED AID ON THIS THESIS

<u>Greg Phillips</u>

Table of Contents

List of Tables

Acknowledgments

I would like to thank Celeste Diaz Ferraro for her support and revisions throughout this whole process, and for all the conversations and meetings we had along the way. My paper would not be where it is today without her help.

I would also like to thank Wade Roberts for his help with my data analysis. His guidance was very helpful in determining what type of regression to use and how to best control for differences related to the starting compositions of census tracts.

INTRODUCTION

Gentrification is widespread and accelerating, and it is changing urban landscapes around the United States. Gentrification directly impacts the physical and social environments that people are exposed to. As neighborhoods undergo gentrification, access and exposure to health resources and risks changes, and the experience of these changes and impact on health outcomes varies across racial and economics lines. Gentrification often forces financially vulnerable residents out of their neighborhood as the cost of living becomes too steep. Research on gentrification and health outcomes can help identify vulnerable populations who experience negative health outcomes because of gentrification and displacement. Studying gentrification and health outcomes can help us better understand the pathways through which neighborhood change affects health. These pathways include physical changes, disruptions to social networks, access to health resources and affordable food options, and stress related to housing insecurity and community disruption. Understanding these pathways can enable more effective intervention from community health initiatives. Additionally, as cities invest in their urban centers, understanding the relationship between gentrification and health outcomes can guide policymakers to develop plans that protect the health and well-being of all residents.

With my research, I aim to understand how displacement because of gentrification impacts health outcomes in Boston. I first explain how gentrification is reshaping urban neighborhoods and how through physical, social, and economic changes this impacts the social and environmental determinants of health that people are exposed to. Development in declining neighborhoods encourages in-migration which changes the community demographic and consequently the community culture. Furthermore, it alters the physical environment of the neighborhood, with new, often more expensive, businesses replacing long-time establishments. The displacement and restructuring of the physical and social environments shape the economic environment. Gentrification leads to rising rents and overall costs of living, displacing low-income residents. I use data from the American Community Survey to understand which census tracts in Boston are gentrifying and where individuals from these tracts are being displaced to. I then use census tract level health data to identify how health outcomes vary between gentrifying tracts compared to tracts where people are displaced to. From this analysis, we can better understand how displacement due to gentrification impacts health and how this impact varies across racial and economic lines. I found that gentrification had a largely beneficial impact on health in the absence of minority residents, but as the percent of minority residents in a gentrifying tract increases, gentrification becomes harmful to health behaviors / risks and outcomes. These findings can help policy makers mitigate risk in areas more susceptible to a negative health impact and help community health initiatives focus their efforts on the most vulnerable areas.

RELEVANT LITERATURE

Gentrification

Gentrification describes the socioeconomic upgrading of urban neighborhoods, characterized by the influx of wealthier residents relative to long-term residents and rising home values and rents (Ding et al. 2016). Gentrification is often framed in terms of class changes, with middle to upper-income residents moving into historically low-income neighborhoods. However, to look at gentrification as a mechanism of class change alone neglects the racialized context in which this process unfolds (Rucks-Ahidiana 2021). Race is necessary to understand the social and political context in which there is contestation over urban neighborhoods (Rucks-Ahidiana 2021). The primary characteristics of gentrification include changes to the built environment through renovation and new construction, rising property values and rents, shifts in businesses and amenities, demographic changes as new residents move-in and long-term residents are displaced, and cultural displacement or erasure as community demographics shift. It is critical to understand that gentrification is not a neutral process, but rather a process with inherent winners and losers, with unequal effects across race and class. The primary stakeholders of gentrification include real estate developers and investors, property owners, local governments, local businesses, new residents, and long-term residents. Integrating race into our understanding of gentrification is critical to understanding power dynamics that create winners and losers. Gentrification benefits homeowners who welcome increases in property value, developers who generate demand and profit from the influx of wealthier residents, new residents who benefit from improved access to amenities, and local governments due to an expanded tax base (Dreier 2017). On the other hand, long-term renters, low-income individuals, and small businesses often bear the costs of gentrification as rising rents and cost of living force their displacement (Versey 2018). Additionally, as new residents move-in and long-term residents are displaced, minority communities experience cultural erasure and loss of social networks (Versey 2018). Understanding the racialized context of gentrification is also necessary to understand when and where gentrification takes place.

Causes of gentrification

Reinvestment in urban neighborhoods is tied to decades of government policy and practices that strategically disinvested in these urban centers leading to the disenfranchisement of minority residents (Mitchell et al. 2024). It is not by chance that these neighborhoods were declining. Racial segregation and discrimination in housing, lending, and lack of infrastructure investment perpetuated cycles of disinvestment in communities of color (Lewis 2021). It is not just redlining by banks and insurance companies that caused the downward spiral of minority neighborhood conditions. City governments used the same tactics, referred to as “Municipal Disinvestment” (Obermiller and Wagner). Cities targeted communities of color using tactics such as “benign neglect” and “planned shrinkage,” strategically reducing public services, closing schools, and neglecting infrastructure in these targeted areas (Obermiller and Wagner).

Redlining along with municipal disinvestment created the conditions necessary for gentrification. Ninety years ago, the Home Owners Loan Corporation (HOLC) created maps which document the Federal Government's development of redlining, formalizing practices of exclusion and lending discrimination (Mitchell et al. 2024). Minority communities were characterized as "subversive" populations that compromised property value and represented a high risk to lenders (Redlining and Health). Redlining established a pattern of strategic disinvestment in minority neighborhoods, creating a cycle of racial and economic segregation (Mitchell et al. 2024). This strategic disinvestment led to neighborhood decay and lower property and land values, making these neighborhoods targets for developers (Cole et al. 2021). Although policies and practices enforcing racial segregation in housing became illegal in 1968 under the Fair Housing Act, the legacies of redlining and disparate treatment of minorities in housing markets persist to today (Rucks-Ahidiana 2021). Formerly redlined neighborhoods are more likely to be higher percentage minority, lower income, have a higher portion of renters, and have lower educational attainment (Redlining and Health). Racial capitalism helps to explain this persistence. Fundamental to the idea of racial capitalism is that capitalism occurs in a racialized context, and race is therefore critical to economic valuations (Rucks-Ahidiana 2021). Through this system, all products, places, and people are associated with a category that exists on a racial hierarchy (Rucks-Ahidiana 2021). This allows racial segregation in housing to persist through the actions of real estate agents and appraisers, banks' decisions on mortgage lending, and white movers' residential preferences (Rucks-Ahidiana 2021). Neighborhoods' racial demographics informed how neighborhoods were viewed and the worth that was assigned to them, ultimately producing the racialized, neglected neighborhoods of today.

The actions of municipalities and lenders caused the neglect and devaluation of minority, urban neighborhoods. This devaluation and decline created an environment that is particularly vulnerable to gentrification. Devaluation creates profit potential: developers often target older, smaller homes in neglected neighborhoods, since they can acquire these properties for well below their redevelopment potential (Munekke and Womack 2014). Redevelopment then makes these neighborhoods more attractive to higher-income residents and increases demand (Levy et al. 2006). Increasing demand for an area creates a feedback loop in which there is greater incentive for developers to increase the housing supply and for new amenities and businesses to open and serve the new, wealthier, often white population (Cole et al. 2021).

The acceleration of gentrification

While research on gentrification began in the mid 20th century, with the term "gentrification" first being introduced by sociologist Ruth Glass in 1964, research on the link between gentrification and health outcomes is a relatively new focus within the academic literature. An increasing number of studies began focusing on the link between gentrification and health since around 2015 (Tulier et al. 2019). By 2010, more than half of all large U.S. cities had at least one gentrifying neighborhood, making the issue more visible to those not directly experiencing it (Schnake-Mahl 2020), and the rate of gentrification across the fifty largest U.S.

cities has nearly doubled, attracting significant attention to this phenomenon in both the media and academic research (Smith et al. 2020). The accelerating rate of gentrification is due in part to an increased demand for urban-living. Fewer people are having children, and more people are having children later in life (Wolfe 2024), making urban life more attractive and accessible to young professionals (Bladen and Mateyka 2023).

How gentrification impacts health outcomes: Pathways of impact

More than individual health is the result of genetics or one's actions, health is the result of societal systems (Redlining and Health). The past and present structural factors that shape neighborhoods affect the social and economic resource distribution, driving current inequities in the distribution of health outcomes (Redlining and Health). Racial residential segregation has been linked to higher prevalence of cardiovascular disease, diabetes, obesity, asthma, and other negative health outcomes (Redlining and Health). The physical and social environments in which people live are important structural drivers of health (Bhavsar et al. 2022). Much of the research on gentrification works to link how gentrification shapes social and environmental determinants of health (SDOH), leading to varying health outcomes among people based on race and socioeconomic status (Bhavsar et al. 2022). SDOH are the conditions where people live, work, and play, and they are profoundly constructed by one's neighborhood. The process through which gentrification impacts health is highly interconnected. Initial investment from developers changes the physical environment of neighborhoods as newer buildings are built and renovations are carried out. This increases demand for housing in the area, and wealthier residents move in, changing the social demographic of the neighborhood. This leads to a second wave of investment in restaurants, retail, and green spaces to serve these new residents, driving up the cost of living and further increasing demand. Increasing demand drives up rents, displacing low-income residents. Furthermore, the influx of new residents creates a shift in consumer preferences, and this coupled with rising rents causes commercial displacement as older establishments and small, local business are forced out. Residential displacement coupled with the in-migration of new residents changes the neighborhood's social environment, leading to exclusion and cultural displacement. Gentrification alters the physical and social environment, driving up costs and causing involuntary displacement, shifting the health risks and opportunities that residents are exposed and have access to.

Physical changes

Although reinvestment in historically declining communities is a seemingly positive trend, the investments associated with gentrification occur because of and to serve the in-migration of wealthier residents due to their spending power (Versey 2018). The physical changes of gentrification along with the influx of wealthier, often white, individuals alter the fabric of neighborhoods. In gentrifying neighborhoods, long-term residents experience a decline in social spaces available to them despite the influx of new business and spaces (Versey 2018).

Black residents living in Central Harlem noticed that many new retail spaces and restaurants were opening around the same time that white, wealthy residents moved in (Versey 2018). They felt that these new spaces catered to the new wealthier, white residents. They noted that while new spaces were opening for some, they saw long-term establishments that catered to them being forced out and closing. Long-term residents saw these new establishments as exclusive spaces; pricey restaurants, cafes, and bars that did not exist for the use or benefit of long-term residents (Versey 2018).

Another physical change associated with gentrification is the creation of green spaces. Green spaces are correlated with higher reported self-health, so in theory the establishment of green spaces in gentrifying neighborhoods would benefit all residents (Cole et al. 2019). However, when adjusting for gentrification, the relationship between green spaces and the lower likelihood of reporting poor health was null (Cole et al. 2019). Only those with higher levels of education, university degree or higher, were found to benefit from new green spaces (Cole et al. 2019). Less advantaged residents did not benefit from the creation of green spaces, suggesting that social exclusion is a determinant of who will benefit from these spaces (Cole et al. 2019). City planners create green spaces in gentrifying neighborhoods because of the influx of wealthier residents, and long-term residents see that city official did not make green spaces until white, wealthier people started moving into their neighborhood, creating the sense that these spaces are not for them (Versey 2018). This in turn enforces social exclusion and causes cultural displacement.

The restructuring of neighborhoods can also lead to a reconfiguration of health resources. For example, the introduction of a high-end grocery stores can force out low-cost options and create a "food mirage", where healthy food options are available but unaffordable for low-income residents. Food mirages are areas with high access to grocery stores, but only ones with high costs which are therefore inaccessible to low-income residents, making the experience for low-income residents equivalent to living in a food desert. Food mirages are most found in low-income areas that have significant increases in the white population (Breyer and Voss-Andreae 2013). Furthermore, food mirages are most extreme in gentrifying areas where higher-cost grocery stores have opened to serve the influx of wealthier residents (Breyer and Voss-Andreae 2013). The combination of food mirages and rising rents cause significant economic pressure for low-income residents, potentially forcing their displacement. This economic barrier can lead to health issues, especially since people's experience of food insecurity is nearly exclusively attributed to financial insecurity (Whittle et al. 2015).

H1a: A higher percentage of the population in gentrifying tracts experiences food insecurity compared to non-gentrifying tracts.

As neighborhoods gentrify, residents can lose or must travel further for their usual sources of health care as either they or their providers are displaced (Cole and Franzosa 2022). Health care gentrification is a shift in the type, location and delivery of urban health care services, and it is a phenomenon associated with gentrification (Cole and Franzosa 2022). Real-estate speculation serves as a key link between health care gentrification and neighborhood gentrification (Cole and Franzosa 2022). Real-estate speculation occurs when developers see profit potential in a failing hospital. The hospital is thought to generate more revenue if converted into housing. In the Fairmount neighborhood of Philadelphia, a gentrifying neighborhood, private equity investors bought St. Joseph's Hospital and are in the process of converting it into housing. This hospital was considered a safety-net hospital, and historically served primarily Black, publicly insured and uninsured patients (Cole and Franzosa 2022). It's closure demonstrates how gentrification perpetuates racial inequity in health care access and outcomes. A similar case happened with St. John's Hospital in Queens, New York; private investors bought the hospital in 2009 and converted it into housing (Parry 2014). The movement and closure of health care service providers along with shifting food access in gentrifying neighborhoods directly impacts resident's access to health resources. Furthermore, the effects of these changes are worse for low-income and minority residents who don't have the same availability of alternatives as higher SES or white residents. Since economic status serves as an inhibitor to accessing health resources, one would expect health outcomes to be worse in low-income neighborhoods.

H1b: A lower percentage of the population in gentrifying tracts go for routine doctor check-ups than non-gentrifying tracts.

Social changes

Changes to the physical environment encourage the in-migration of wealthier residents, which changes the neighborhood's social demographic. One's social environment has a profound impact on their well-being and ability to manage both stress and physical ailments (Carr 2018). As the demographic of a neighborhood changes so do residents' social capital and the community culture (Versey 2018). This can lead to social exclusion and negatively impact mental health (Versey 2018). Black seniors living in Central Harlem said that the racial composition of their neighborhood was shifting because of gentrification (Versey 2018). This change left these long-term residents feeling out of place and unwanted (Versey 2018). Participants stated that exchanges between social groups largely did not occur.

The changing social environment within gentrifying neighborhood changes the community's cultural dynamics as social norms change and trust degrades (Versey 2018). The displacement of long-term residents from gentrifying neighborhoods further alters the social environment. This shift in the social environment breaks down the social capital of long-term residents, causing increased isolation (Versey 2018). Social exclusion can lead to increased stress and reduced access to community resources. Additionally, social networks have been shown to improve positive health behaviors and outcomes while reducing the risk of adverse health outcomes in many studies (Foong et al. 2021, Braren 2023 Ellward et al. 2019). Adults living in gentrifying neighborhoods have been shown to have higher rates of anxiety and depression (Bhavsar et al. 2022), likely due to the breakdown of social networks and loss of community ties.

Those that are displaced from gentrifying neighborhoods tend to already be the most vulnerable, and involuntary displacement from one's community represents an even more significant disruption to one's social environment than that from the social shifts within gentrifying neighborhoods. Therefore, one would expect that adverse health consequences due to social network breakdown are worse for displaced residents compared to residents in gentrifying neighborhoods. Increased social isolation due to the changing social environment may also lead residents to cope with stressors in less healthy ways.

H1c: Gentrifying tracts have higher percentage of people experiencing low social and emotional support than non-gentrifying tracts.

H1d: A higher percentage of the population in gentrifying tracts experience depression compared to non-gentrifying tracts.

H1f: A higher percentage of the population in gentrifying tracts experience social isolation compared to non-gentrifying tracts.

H1g: A higher percentage of the population in gentrifying tracts binge drinks compared to non-gentrifying tracts.

The impact of stress on health

Gentrification is stressful for long-term residents. Residents of gentrifying neighborhoods see their neighborhood's social demographic and culture change as new residents move in and neighbors and friends are forced out. They experience the loss of community establishments as consumer preferences change and new businesses open, forcing out small, local businesses. They see the cost-of-living increase because of the physical and social changes forced upon their neighborhood. This increase represents a significant financial burden for low-income residents and causes stress. Psychosocial stress a significant risk factor when looking at negative health behaviors, health outcomes, and as a mediator between low socioeconomic status (SES) and health (Schmool et al. 2015), so stress is one of the ways that gentrification is linked to health outcomes. Residents of gentrifying neighborhoods have cited that their experience of gentrification is a significant source of stress (Schmool et al. 2015), and they express a feeling of sadness and loss for their neighborhood and community. On top of this, landlords are cited to be neglectful to long-term residents in gentrifying neighborhoods, causing a feeling of powerlessness among tenants (Schmool et al. 2015).

Gentrification has also been shown to increase the police presence in neighborhoods (Santos et al. 2021). This seemingly is a positive change since it would reduce or deter crime. However, among Black Americans, police interactions were associated with a twofold higher prevalence of poor mental health compared to those with no police interactions (McLeod et al. 2019). Additionally, a study conducted with minority New York residents found that police and safety, and gentrification and racism were the primary social stressors in residents' daily lives (Schmool et al. 2015). Residents stated that the police would bother them while they were simply trying to mind their business, and residents expressed concern for their safety given the prevalence of police brutality on people of color (Schmool et al. 2015). Thus, gentrification, through several mechanisms, represents a source of stress in the lives of long-term residents, especially among minority residents and low-income residents who face stress from police presence and financial insecurity respectively.

Research has shown that stress negatively impacts mental health, with stress increasing rates of depression, anxiety, and other mental health issues (Almeida 2024). Since gentrification involves significant disruption to the lives and communities of long-term residents and has been cited to be a source of stress (Schmool et al. 2015), one would expect those experiencing gentrification or displacement due to gentrification to be at a higher risk for negative mental health outcomes.

H1e: A higher percentage of the population in gentrifying tracts experience frequent mental distress compared to non-gentrifying tracts.

Economic changes

The physical and social changes that occur in gentrifying neighborhoods increase demand and lead to an increase in property values and rents (Franco et al. 2019). This reduces the supply of affordable housing, and ultimately drives up the cost of living. Increased living costs reduce the ability of disadvantaged residents to pay for health resources, creating a potential health risk among this group (Delong 2023). Additionally, the intrusion of retail spaces catering to new residents changes the commercial landscape of the neighborhood, impeding low-income residents' ability to get living necessities (Delong 2023). The increase in the portion of income spent on housing also reduces residents' ability to pay for food, leading to greater food insecurity especially when considering the association between food mirages and gentrifying neighborhoods. This leads to higher risks of malnutrition and other negative health outcomes (Whittle et al. 2015). Rising livings costs ultimately lead to the displacement of low-income residents as they are priced out of their own neighborhood.

Variation in mobility and displacement

Residents having to move out of their neighborhood due to gentrification are constrained in their search since they tend to be lower income. Therefore, it is worth examining the quality of the residential move that is occurring (Delong 2023). Among all movers, financially vulnerable individuals are more likely to make a downward move, move to a neighborhood with a lower median income (Ding et al. 2017). Additionally, low-income movers moving out of a gentrifying neighborhood are more likely to move to a lower income neighborhood when compared to similar residents moving from non-gentrifying neighborhoods (Ding et al. 2017). The degree to which gentrification is occurring in the neighborhood intensifies this phenomenon, meaning that already disadvantaged residents are even more likely to move to economically worse neighborhoods when gentrification is more intense. Over time, higher living costs are likely to force vulnerable residents out of their neighborhood, and when vulnerable individuals are moving out of intensely gentrified neighborhoods the likelihood that this is a downward move is high. Furthermore, residents who are unable to remain in their neighborhood due to rising costs are likely to be constrained in their housing search as gentrification occurs throughout their city, reducing the supply of affordable housing. This involuntary displacement represents a significant disruption to the lives and communities of vulnerable residents. Since residents moving out of gentrifying neighborhoods are ending up in a more disadvantaged area, their exposure to health risks increases. Furthermore, involuntary displacement likely leads to adverse mental health outcomes related to stress and financial insecurity. Since displacement varies across race and class, it is likely that it functionally reinforces health inequities. Since the history of racial residential segregation created neighborhoods which are prone to gentrification, it is likely that as gentrification occurs, long-term minority residents are forced out of their homes.

H4a: The percent of minority residents is lower in more intensely gentrified tracts compared to non-gentrifying tracts.

H4b: The percent of Black residents is lower in more intensely gentrified tracts compared to non-gentrifying tracts.

Does gentrification perpetuate health inequities?

The social and economic resource distribution, shaped by one's neighborhood, create disparities in the distribution of health outcomes. Gentrification reshapes the social and economic resource distribution, changing the sort of access / exposure that residents have as residential and commercial displacement takes place. While it is understood that the history of redlining and racial residential segregation fuel gentrification, and that the effects of gentrification vary across racial and class lines, it is unclear how displacement from gentrifying neighborhoods impacts health outcomes. I am asking in this study how displacement from gentrifying neighborhoods and race and class interact to perpetuate health inequalities. I predict that displacement due to gentrification is positively associated with adverse health outcomes, meaning that the health outcomes among displaced individuals are worse compared to those in gentrifying tracts, and that displacement functionally reinforces health inequity. If displacement varies by race, and health outcomes in displacement tracts are worse, then we would expect that the impact of gentrification on health varies for different racial groups.

H2: The percent of minority residents is associated with an increase in the percent of the population experiencing the previously considered health outcomes in gentrifying tracts.

H3: The percent of minority residents is associated with an increase in the percent of the population experiencing the previously considered health outcomes in gentrifying tracts.

DATA

To test these hypotheses, I chose to take a quantitative approach. Using a quantitative approach allows for a granular analysis of how displacement, gentrification, and health outcomes are related to each other. For the purpose of this study, I focus on gentrification in Boston. Boston provides an interesting case study since it has been ranked as the third most gentrified city in the U.S. (NCRC 2021). Furthermore, Boston has a history of racial and economic segregation, and with a booming economy and large student population, which can constrain housing supply, it is incredibly vulnerable to gentrification. Boston exhibits extreme levels of economic inequality between new-comers and long-term residents, and due to a constrained housing supply, gentrification has driven up rents and forced the displacement of many long-term residents in areas such as Roxbury, Dorchester, and East Boston (The Daily Free Press 2021). This has created significant changes in the community demographics and physical environments of these neighborhoods, making Boston a prime area to focus on for the aims of my study.

Data for this study comes from the American Community Survey (ACS) and CDC dataset PLACES: Local Data for Better Health for the years of 2010-2022 and 2021-2022 respectively. Both datasets include census tract level information, allowing for an analysis of gentrification and its impacts at this level. Census tracts generally have several thousand residents; of those that I am looking at the minimum population is 8, the maximum population is 9455, and the median is 3545.5. For this study, I determine which tracts are gentrifying tracts and which are displacement tracts (tracts where displaced residents from gentrifying tracts move to) using the mobility and housing ACS datasets. I then use health outcome data from PLACES: Local Data for Better Health to see how the distribution of health outcomes varies between these identified tracts.

In identifying relevant census tracts, I determine which tracts are gentrifiable, gentrifying, non-gentrifying, and destinations for displaced residents. To do so, I use variable stand-ins for the phenomenon of gentrification. I adopt the criteria for census tract characterization developed in Ding and colleagues' (2016) study of gentrification and mobility in Philadelphia. *Gentrifiable* tracts are census tracts that could experience gentrification; these tracts have a median household income below the citywide median at the beginning of the period of analysis, 2018 in my case. For a tract to be *gentrifying,* one experiencing gentrification, it must meet the following criteria. The tract must be gentrifiable at the beginning of the analysis *and* have an above citywide median percentage increase in either its median home value *or* median rent *and* have an above citywide median increase in share of college educated residents. *Non-gentrifying* tracts are those that are gentrifiable based on the previous definition but fail to meet the gentrifying criteria. More on my variables and their components can be found in table 1.

Since gentrification is a dynamic and occurs as a stage-like process Ding et al. used subcategories for gentrifying areas to reflect these differences. They categorized tracts that gentrified from 1980 to 2000 *and* were gentrifying from 2000-2013 as *continued gentrification*. They also broke down gentrifying tracts by intensity. While I don't have data before 2010 and therefore cannot assess whether this gentrification represents *continued gentrification*, I do have the necessary data to categorize gentrification intensity. I construct the variable for level of gentrification using the following components: median income, median home value, median rent, and educational attainment, adopting the same categories used in Ding and colleagues' (2016) study. They rate the level of gentrification as weak, moderate, or intense. *Weak gentrification* constitutes gentrifying tracts that are in the bottom quartile of gentrifying tracts for rent and home value during the period of analysis. *Moderate gentrification* constitutes gentrifying tracts in either the second or third quartile for rent and value, and *Intense gentrification* constitutes tracts in the top quartile for rent and value. Categorizing the intensity of gentrification is important for my study since it allows for us to have a more nuanced view and analysis on the relationship between gentrification and health outcomes.

While previous studies have not looked at the tracts where displaced residents move to, a study by Lim et al. looked at displaced residents and defined them as those who had ever moved to a non-gentrifying, poor neighborhood (Lim et al. 2017). Building on this interpretation of displacement, I define *displacement tracts* as those that are non-gentrifying based on the previous definition *and* have an above citywide median increase of new residents during the period of analysis.

I include demographic information on race, percent minority and percent Black, to see what sort of effect race has on the relationship between displacement, gentrification, and health outcomes. This is important to see how displacement and gentrification may reinforce issues of health inequity. The health outcomes that I include are heart disease, depression, food insecurity, lack of social and emotional support, binge drinking, high blood pressure, short sleep duration, fair or poor self-rated health, visits to a doctor for routine check-ups in past year, and frequent mental distress. I include a wide range of both physical and mental health outcomes to see how the impact of displacement and gentrification functions on different conditions. These health outcomes relate back to the pathways of impacts and the ways in which gentrification alters SDOHs.

DATA CLEANING

My primary challenge when it came to data cleaning was discrepancies in the census tract boundaries between years. To determine the gentrification status of each tract I needed complete data across all year, 2010 to 2022. While I did not run into issues with most tracts, there were 20 tracts that were present from 2010-2018 and missing 2019 onwards. To correct for the tract splits that occurred between 2018 and 2019, I found maps of the two versions of the boundaries (a 2010 tract map and 2020 tract map) and aggregated split tracks back to the boundaries used at the beginning period of my analysis. Additionally, I checked population total in years 2018 and 2019 for those areas to test if the aggregation of split tracts is feasible. Table 2 includes these relevant tracts as well as population totals. For my study, I focused on cleaning census tracts located in neighborhoods that had previously been identified as gentrifying in a Harvard study on mapping neighborhood change in Boston (Hermann et al. 2019).

Table 1: Aggregating split census tracts located in gentrifying neighborhoods

Original tract	Neighborhood	2018 population	Split tracts	2019 aggregate population
612	South Boston	4544	61201, 61203, 61204	4746
705	South End	5761	70501, 70502	6017
708	South End	3555	70801, 70802	3537
709	South End	3087	70901, 70902	3072
813	Roxbury	4885	81301, 81302	4708
10203	Fenway	5596	10205, 10206	5853
110103	Jamaica Plains	6674	110104, 110105, 110106	6875

Using the maps of the different census tract boundaries I was able to see geographic how these tracts split and what the new tract numbers were. Having the population total serve as a check, allowed me to understand if this aggregation back to the original tract was an appropriate solution.

When aggregating split tracts, I had to sum certain variables while averaging others. If the variable included a raw count of some characteristic (total population, White, Moved in the last year, etc.) I summed the variable across the splits tracts. If the variable included a median or a percent (median age, median income, median home value, median rent, percent of the population experiencing depression, etc.) then I average the variable amongst the split tracts. This allowed me to generate the relevant variables and obtain complete data across all years for the relevant census tracts. The code that I used to aggregate split tracts can be found in appendix a.

DATA ANALYSIS

For my analysis, I ran multiple linear regressions to test my hypotheses and understand the relationship between gentrification, displacement, and health outcomes. I chose to use an OLS regression since gentrification status is a fixed characteristic of each census tract in my dataset. Since gentrification status doesn't vary over time, an OLS model allows me to directly estimate the effect of different gentrification statuses (weak, moderate, intense, etc.) on health outcomes. Additionally, since I was working with a cross-sectional dataset, an OLS regression is the most suitable option. Gentrification status was a categorical variable, and I set non-gentrifying as the reference group. I included control variables to isolate the effect of gentrification on health outcomes. I controlled for the tract composition at the starting point so that I could isolate the effect of gentrification status. The controls that I used are all from the ACS 2008-2012 5-year aggregate, and include median age, percent white, percent Black, percent Asian, percent Latino, percent with a bachelor's degree or higher, median household income, percent owner occupied, and percent living below the poverty line. I regressed population health measures at time 2 (2022) against demographic characteristics at time 1 (08-12 5-yr aggregate) and gentrification status. I used robust standard errors to correct for heteroskedasticity, avoiding biased standard errors and providing me with more reliable results. My hypotheses and the models I used to test them are outlined below.

Table 1 includes all the relevant variables that I used in my analysis as well as their components and what they represent.

Table 2: variable table

Variable	**Components**	**What it represents**
Gentrifiable	Median income	Whether or not a census tract can experience gentrification. If the median income is below the citywide medianincome at the start of the analysis, then the tract is gentrifiable.
Gentrifying	Median home value, median rent, educational attainment	Whether or not a census tract is experiencing gentrification. To meet the critieria the census tract must be gentrifiable by the above

		criteria *and* have an above citywide median percentage increase in either its median home value *or* median rent *and* have an above citywide median increase in share of college educated residents.
Weakly gentrified	Median rent or home value	Tract is gentrifying and is in the bottom quartile in terms of median rent or home value among gentrifying tracts
Moderately gentrified	Median rent or home value	Tract is gentrifying and is in the 2nd or 3rd quartile in terms of median rent or home value among gentrifying tracts
Intensely gentrified	Median rent or home value	Tract is gentrifying and is in the top quartile in terms of median rent or home value among gentrifying tracts
Non-gentrifying	Median income, median home value, median rent, educational attainment	The census tract is gentrifiable by the previous conditionas but fails to meet the conditions to be considered gentrifying.
Displacement tract	Moved in the last year	The census tract is non-gentrifying by the previous definition *and* has an above citywide median number of residents moving in over the period of the analysis.
Moved in the last year	Movedinthelastyear	The number of residents that moved into the census tract in the last year.
Year	Year	The year.
pMinority22	Total population, white non-Hispanic	The percent of the census tract population that is non-white.
pBlack22	Total population, Black or African American	The percent of the population that is Black.

CHD	Coronary heart disease among adults	The percent of the census tract age >=18 that experience coronary heart disease.
Depression	Depression among adults	The percent of the census tract age >=18 who responded yes to having ever been told by a doctor, nurse, or other health professional they had a depressive disorder, including depression, major depression, dysthymia, or minor depression.
Food insecurity	Food insecurity in the past 12 months	The percent of the census tract who reported that the food that they bought always/usually/sometimes did not last, and they didn't have money to get more.
Lack of social and emotional support	Lack of social and emotional support	The percent of the census tract who report sometimes, rarely, or never getting the social and emotional support needed.
Binge drinking	Bing drinking among adults	The percent of the census tract age >=18 who report having $\geq$ 5 drinks (men) or $\geq$ 4 drinks (women) on $\geq$ 1 occasion during the previous 30 days.
Short sleep duration	Short sleep duration among adults	The percent of the census tract age >=18 that get less than 7 hours of sleep per night.
Fair or poor self-rated health	Fair or poor self-rated health	The percent of the census tract that report their health as fair or poor.
Routine doctor visits	Visits to the doctor for routine checkups in the past year	The percent of the census tract who report having been to a doctor for a routine checkup (e.g., a general

		physical exam, not an exam for a specific injury, illness, or condition) in the previous year.
Frequent mental distress	Frequent mental distress among adults	The percent of the census tract age >=18 who report that their mental health (including stress, depression, and problems with emotions) was not good for 14 or more days during the past 30 days.
Socially isolated	Feeling socially isolated	The percent of the census tract age >=18 who report feeling socially isolated
Medage0812	Median age	The median age for 2008-2012 aggregate
Pwhitenh0812	Percent White, non-Hispanic	The percent of the population that is White, non-Hispanic, for the 2008-2012 aggregate
Pblacknh0812	Percent Black, non-Hispanic	The percent of the population that is Black, non-Hispanic, for the 2008-2012 aggregate
Pasiannh0812	Percent Asian, non-Hispanic	The percent of the population that is Asian, non-Hispanic, for the 2008-2012 aggregate
Platino0812	Percent Latino	The percent of the population that is Latino for the 2008-2012 aggregate
Pbachup0812	Percent with bachelor's degree or higher	The percent of the population that has a bachelor's degree or higher for the 2008-2012 aggregate
Mhi0812	Median household income	The median household income for the 2008-2012 aggregate
Pownocc0812	Percent of owner-occupied units	The percent of the occupied housing units that are owner occupied for the 2008-2012 aggregate

Ppov0812	Percent of population living below the poverty line	The percent of the population that living below the poverty line for the 2008-2012 aggregate

HYPOTHESES AND MODELS

My first set of hypotheses (H1) aim to understand then test how gentrification impacts health outcomes and behaviors / risks. My second and third set of hypotheses (H2 and H3) aim to test an understand how race interacts with gentrification status to impact health. My fourth set of hypotheses (H4) aim to test and understand how gentrification impacts the racial composition.

H1: Testing the impact of gentrification on health

The general model that I used to test my H1 hypotheses is

$$Health_{2022} = \beta 0 + \beta 1 * MedAge_{08-12} + \beta 2 * pWhitenh_{08-12} + \beta 3 * pBlacknh_{08-12} + \beta 4 * pAsiannh_{08-12} + \beta 5 * pLatino_{08-12} + \beta 6 * pBachup_{08-12} + \beta 7 * MHI_{08-12} + \beta 8 * pOwnOcc_{08-12} + \beta 9 * pPov_{08-12} + \beta 10 * GentrificationStatus + \epsilon$$

H1a: A higher percentage of the population in gentrifying tracts experiences food insecurity compared to non-gentrifying tracts.

$$FoodInsecurity_{2022} = \beta 0 + \beta 1 * MedAge_{08-12} + \beta 2 * pWhitenh_{08-12} + \beta 3 * pBlacknh_{08-12} + \beta 4 * pAsiannh_{08-12} + \beta 5 * pLatino_{08-12} + \beta 6 * pBachup_{08-12} + \beta 7 * MHI_{08-12} + \beta 8 * pOwnOcc_{08-12} + \beta 9 * pPov_{08-12} + \beta 10 * GentrificationStatus + \epsilon$$

H1b: A lower percentage of the population in gentrifying tracts go for routine doctor check-ups than non-gentrifying tracts.

$$RoutineCheckups_{2022} = \beta 0 + \beta 1 * MedAge_{08-12} + \beta 2 * pWhitenh_{08-12} + \beta 3 * pBlacknh_{08-12} + \beta 4 * pAsiannh_{08-12} + \beta 5 * pLatino_{08-12} + \beta 6 * pBachup_{08-12} + \beta 7 * MHI_{08-12} + \beta 8 * pOwnOcc_{08-12} + \beta 9 * pPov_{08-12} + \beta 10 * GentrificationStatus + \epsilon$$

H1c: Gentrifying tracts have higher percentage of people experiencing low social and emotional support than non-gentrifying tracts.

$$LackOfSupport = \beta 0 + \beta 1 * MedAge_{08-12} + \beta 2 * pWhitenh_{08-12} + \beta 3 * pBlacknh_{08-12} + \beta 4 * pAsiannh_{08-12} + \beta 5 * pLatino_{08-12} + \beta 6 * pBachup_{08-12} + \beta 7 * MHI_{08-12} + \beta 8 * pOwnOcc_{08-12} + \beta 9 * pPov_{08-12} + \beta 10 * GentrificationStatus + \epsilon$$

H1d: A higher percentage of the population in gentrifying tracts experience depression compared to non-gentrifying tracts.

$$Depression_{2022} = \beta 0 + \beta 1 * MedAge_{08-12} + \beta 2 * pWhitenh_{08-12} + \beta 3 * pBlacknh_{08-12} + \beta 4 * pAsiannh_{08-12} + \beta 5 * pLatino_{08-12} + \beta 6 * pBachup_{08-12} + \beta 7 * MHI_{08-12} + \beta 8 * pOwnOcc_{08-12} + \beta 9 * pPov_{08-12} + \beta 10 * GentrificationStatus + \epsilon$$

H1e: A higher percentage of the population in gentrifying tracts experience frequent mental distress compared to non-gentrifying tracts.

$$FrequentDistress_{2022} = \beta 0 + \beta 1 * MedAge_{08-12} + \beta 2 * pWhitenh_{08-12} + \beta 3 * pBlacknh_{08-12} + \beta 4 * pAsiannh_{08-12} + \beta 5 * pLatino_{08-12} + \beta 6 * pBachup_{08-12} + \beta 7 * MHI_{08-12} + \beta 8 * pOwnOcc_{08-12} + \beta 9 * pPov_{08-12} + \beta 10 * GentrificationStatus + \epsilon$$

H1f: A higher percentage of the population in gentrifying tracts experience social isolation compared to non-gentrifying tracts.

$$SociallyIsolated_{2022} = \beta 0 + \beta 1 * MedAge_{08-12} + \beta 2 * pWhitenh_{08-12} + \beta 3 * pBlacknh_{08-12} + \beta 4 * pAsiannh_{08-12} + \beta 5 * pLatino_{08-12} + \beta 6 * pBachup_{08-12} + \beta 7 * MHI_{08-12} + \beta 8 * pOwnOcc_{08-12} + \beta 9 * pPov_{08-12} + \beta 10 * GentrificationStatus + \epsilon$$

H1g: A higher percentage of the population in gentrifying tracts binge drinks compared to non-gentrifying tracts.

$$BingeDrink_{2022} = \beta 0 + \beta 1 * MedAge_{08-12} + \beta 2 * pWhitenh_{08-12} + \beta 3 * pBlacknh_{08-12} + \beta 4 * pAsiannh_{08-12} + \beta 5 * pLatino_{08-12} + \beta 6 * pBachup_{08-12} + \beta 7 * MHI_{08-12} + \beta 8 * pOwnOcc_{08-12} + \beta 9 * pPov_{08-12} + \beta 10 * GentrificationStatus + \epsilon$$

H1h: A higher percentage of the population in gentrifying tracts experience a short sleep duration compared to non-gentrifying tracts.

$$ShortSleep_{2022} = \beta 0 + \beta 1 * MedAge_{08-12} + \beta 2 * pWhitenh_{08-12} + \beta 3 * pBlacknh_{08-12} + \beta 4 * pAsiannh_{08-12} + \beta 5 * pLatino_{08-12} + \beta 6 * pBachup_{08-12} + \beta 7 * MHI_{08-12} + \beta 8 * pOwnOcc_{08-12} + \beta 9 * pPov_{08-12} + \beta 10 * GentrificationStatus + \epsilon$$

H1i: A higher percentage of the population in gentrifying tracts rate their health as fair or poor compared to non-gentrifying tracts.

$$FairOrPoorSRH_{2022} = \beta 0 + \beta 1 * MedAge_{08-12} + \beta 2 * pWhitenh_{08-12} + \beta 3 * pBlacknh_{08-12} + \beta 4 * pAsiannh_{08-12} + \beta 5 * pLatino_{08-12} + \beta 6 * pBachup_{08-12} + \beta 7 * MHI_{08-12} + \beta 8 * pOwnOcc_{08-12} + \beta 9 * pPov_{08-12} + \beta 10 * GentrificationStatus + \epsilon$$

For the H2 set I tested the same health behaviors and outcomes but included an interaction term for percent minority. I predict that percent minority will be positively associated with negative health outcomes in gentrifying tracts. The general equation that I used was

$$\boldsymbol{H2}\text{:}\ Health_{2022} = \beta 0 + \beta 1 * MedAge_{08-12} + \beta 2 * pWhitenh_{08-12} + \beta 3 * pBlacknh_{08-12} + \beta 4 * pAsiannh_{08-12} + \beta 5 * pLatino_{08-12} + \beta 6 * pBachup_{08-12} + \beta 7 * MHI_{08-12} + \beta 8 * pOwnOcc_{08-12} + \beta 9 * pPov_{08-12} + \beta 10 * GentrificationStatus * pMinority_{2022} + \epsilon$$

For each specific model I simply changed the health outcome, the dependent variable.

For the H3 set I tested same health variables and tested the interaction between percent Black and gentrification status. I predict that percent Black will be positively associated with negative health outcomes in gentrifying tracts. The general equation that I used was

$\boldsymbol{H3}$: $Health_{2022} = \beta 0 + \beta 1 * MedAge_{08-12} + \beta 2 * pWhitenh_{08-12} + \beta 3 * pBlacknh_{08-12} + \beta 4 * pAsiannh_{08-12} + \beta 5 * pLatino_{08-12} + \beta 6 * pBachup_{08-12} + \beta 7 * MHI_{08-12} + \beta 8 * pOwnOcc_{08-12} + \beta 9 * pPov_{08-12} + \beta 10 * GentrificationStatus * pBlack_{2022} + \epsilon$

Lastly, for H4 I tested the impact of gentrification status on racial composition, specifically looking at percent minority and percent Black.

H4a: The percent of minority residents is lower in more intensely gentrified tracts compared to non-gentrifying tracts.

$$pMinority_{2022} = \beta 0 + \beta 1 * MedAge_{08-12} + \beta 2 * pWhitenh_{08-12} + \beta 3 * pBlacknh_{08-12} + \beta 4 * pAsiannh_{08-12} + \beta 5 * pLatino_{08-12} + \beta 6 * pBachup_{08-12} + \beta 7 * MHI_{08-12} + \beta 8 * pOwnOcc_{08-12} + \beta 9 * pPov_{08-12} + \beta 10 * GentrificationStatus + \epsilon$$

H4a: The percent of Black residents is lower in more intensely gentrified tracts compared to non-gentrifying tracts.

$$pBlack_{2022} = \beta 0 + \beta 1 * MedAge_{08-12} + \beta 2 * pWhitenh_{08-12} + \beta 3 * pBlacknh_{08-12} + \beta 4 * pAsiannh_{08-12} + \beta 5 * pLatino_{08-12} + \beta 6 * pBachup_{08-12} + \beta 7 * MHI_{08-12} + \beta 8 * pOwnOcc_{08-12} + \beta 9 * pPov_{08-12} + \beta 10 * GentrificationStatus + \epsilon$$

SUMMARY STATISTICS

I calculated two sets of summary statistics. One for the dataset used in determining gentrification status (this dataset includes data ACS data from 2010-2022), and one for the dataset that I used to test my models (this dataset includes health outcomes as well as baseline demographic data from the 2008-2012 5-year aggregates).

Table 3: Summary statistics for gentrification status dataset

Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Year	2,184	2016	3.742514	2010	2022
CensusTract	2,184	45,575.35	91,389.48	103	980,101
Totalpopulation	2,184	3,832.287	1,423.212	287	9,455
Black or African	2,184	938.9876	1,222.708	0	6,811
White alone	2,184	1,706.804	1,207.371	0	5,218
Higher Education	2,184	1,116.25	770.5201	3	4,273
Moved in last year	2,184	322.956	610.1558	0	5,476
Median Age (years)	2,184	34.32392	6.343302	19.5	60.3
Median Income ($)	2,172	35,053.17	19,055.95	2,576	146,579
Median Home Value	2,184	295,117.4	353,253.9	0	1,747,000
Median Gross Rent	2,184	882.7357	991.9952	0	5,147
Median Home Equity	2,106	74.5228	58.69932	-100	327.3585
Median Gross Rent % increase	2,158	59.4369	62.11958	-100	509.5324
Higher Education % increase	2,184	124.6322	198.2197	0	1,423.595
Gentrification Status	1,482	2.905533	1.223993	1	5

Table 4: Summary statistics for regression dataset

Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
CensusTract	50	82202.14	57210.08	202	170702
Totalpopulation	50	4467.34	1348.89	1701	7350
BlackorAfrican	50	881.58	1094.53	31	4431

Whitealone	50	1660.42	902.04	45	3585
HigherEducation	50	1240.10	735.25	237	3070
Movedinlastyear	50	565.06	302.25	91	1332
Medianincome	50	35408.93	15413.54	5458	64167
Medianhomevalue	50	593056.70	380583.30	0	1747000
Mediangrossrent	50	1837.59	778.48	0	4441
Gentrification	50	3.40	1.51	1	5
Poptot0812	50	4206.96	1257.48	1727	6767
Medage0812	50	31.63	6.97	19.80	47.40
Pwhitenh0812	50	42.60	22.15	1.40	79.67
Pblacknh0812	50	19.39	22.60	0.90	89.75
Pasiannh0812	50	12.32	12.35	0.00	69.66
Platino0812	50	22.84	16.76	4.08	70.77
Pbachup0812	50	36.52	22.82	4.46	84.32
Mhi0812	50	40440.98	16648.69	12921	72390
Pownocc0812	50	28.26	19.73	0.00	78.04
Ppov0812	50	28.28	15.78	4.53	63.98
NewCHD	50	4.99	1.81	1.00	9.80
Newdepression	50	24.53	2.70	20.30	31.80
Newfoodinsecure	50	20.34	8.07	7.50	36.90
Newlackofsleep	50	28.10	3.50	21.20	34.80
Newbingedrinking	50	19.47	3.00	14.00	26.00
Newshortsleep	50	34.79	3.55	28.20	42.90
Newfairpoorhealth	50	17.56	5.60	7.00	30.40
Newdocvisits	50	75.20	3.36	70.10	82.90
Newmentaldistress	50	19.70	3.60	14.00	29.30
Newsocialisolated	50	38.36	3.24	33.30	46.10
PBlack22	50	19.22	20.84	0.79	79.54
PMinority22	50	61.29	19.32	32.88	99.28

RESULTS

Table 5: Summary of results

Hypothesis	**Supported / Not support**
Gentrification status is negatively associated with the percent of minority residents relative to non-gentrifying tracts.	Supported
Gentrification status is negatively associated with the percent of Black residents relative to non-gentrifying tracts.	Supported
Gentrification status is positively associated with adverse health behaviors and outcomes relative to non-gentrifying tracts.	Not supported
The percent of minority residents living in gentrified tracts is positively associated with adverse health behaviors and outcomes relative to non-gentrifying tracts.	Supported
The percent of Black residents living in gentrified tracts is positively associated with adverse health behaviors and outcomes relative to non-gentrifying tracts.	Supported

As gentrification continues and becomes more mature in areas, minority and Black residents are pushed out.

Table 6 includes the results from my models testing the relationship between race and gentrification status relative to non-gentrifying tracts. I found no statistically significant evidence that the percent of minority or percent of black residents decreases as the intensity of gentrification increases. In the model that tested the effect on the percent of the residents that are minorities, as gentrification status increased from weak to intense, the relationship flipped from positive to negative. A weakly gentrified tract was associated with a 2.8% increase in the percent of minority residents. Moderately and intensely gentrified tracts were associated with a 1.25% and 7.8% decrease in the percent of minority residents respectively. Additionally, displacement tracts were associated with a 4.7% increase in the percent of minority residents. A similar trend is notable in the results that tested the effect of gentrification on the percent of Black residents. Although not statistically significant, the directions of these relationships demonstrated that more intensely gentrified tracts ten to have a smaller percentage of minority and black residents compared to non-gentrified tracts. Additionally, displacement tracts have a higher percentage of minority and black residents compared to non-gentrifying tracts. This makes sense given what we know broadly about income, educational attainment, and homeownership rates among minorities living in historically low-income areas. As the gentrification matures and the intensity increases, many of the mechanisms through which gentrification forces displacement have the time to fully develop. Intensely gentrified tracts have higher rents, causing economic displacement as renters are forced to move-out or allocate a larger portion of their incomes to rent. Additionally, as residents are forced out, there is greater breakdown in previously existing social networks.

Table 6: Effects of gentrification status on racial demographics

Predictors	pMinority22	pBlack22
Controls for starting composition		
Median Age	-0.654*** (-2.83)	-0.2265 (-0.98)
Percent white	-1.061* (-1.83)	-0.2333 (-0.56)
Percent Black	-0.4343 (-0.74)	0.6541 (1.51)
Percent Asian	-0.6611 (-1.00)	-0.1315 (-0.28)
Percent Latino	-0.4959 (-0.86)	-0.2729 (-0.63)
Educational attainment	-.3089**** (-3.47)	-0.0915 (-1.34)
Median household income	-0.0001 (-0.77)	0.0001 (0.50)
Percent owner occupied	-0.0135 (-0.12)	-0.0626 (-0.72)
Percent impoverished	-0.2065 (-1.06)	-0.1624 (-1.01)

Gentrification status		
Weakly gentrified	2.8114 (0.62)	1.0221 (0.28)
Moderately gentrified	-1.2518 (-0.39)	0.5142 (0.19)
Intensely gentrified	-7.7755 (-1.24)	-6.7935 (-1.29)
Displacement tract	4.707* (1.81)	4.1951 (1.48)
Y-intercept	175.869** (2.68)	37.0115 (0.79)
R^2	.9137	.8074

Notes: Robust t-statistics in parentheses.

*P < .10 **P < .05 ***P < .01 ****P < .001

Gentrification status alone was primarily associated with a decrease in negative health behaviors and outcomes.

Table 7 shows the effects of gentrification status on health behaviors, health risks, and health outcomes relative to non-gentrifying tracts. I found no support for H1a, which predicted that gentrification would lead to a higher percentage of the population experiencing food insecurity. In fact, intensely gentrifying tracts were found to have an 8% decrease, with significance at the 5% level, in food insecurity relative to non-gentrifying tracts. My controls worked as expected, with a one percent increase in the percent of bachelor's degrees or above resulting in 0.2% decrease, significant at the 1% level, in the percent of the population experiencing food insecurity. Additionally, a one percent increase in the percent of people living below the poverty resulted in a 0.17% increase, significant at the 1% level, in the percent of people experiencing food insecurity.

I found weak support for H1b, which predicted that a lower percentage of the population would report going for routine doctor checkups in gentrifying tracts than in non-gentrifying tracts. Although support for this relationship was weaker, the direction of the relationship was consistent with my predictions. That is, moderately and intensely gentrifying tracts saw a decrease in the percent of population having routine checkups. Furthermore, displacement tracts were associated with a 1% decrease, significant at the 5% level, in the percent of the population going for routine doctor checkups.

H1c suggested that gentrifying tracts had a higher percentage of their population who experienced a lack of social and emotional support compared to non-gentrifying tracts. I did not find any strong relationship here. There was a weak but significant relationship between a couple of the controls. A one year increase in median age is associated with a .2% decrease, significant at the 1% level, in the percent of the population experiencing a lack of social and emotional support, and a one percent increase in the percent of the population with a bachelor's degree or higher was associated with a .1% decrease, significant at the .1% level, in the percent of the population experiencing a lack of social and emotional support.

There was no support for H1d, which predicted that a higher percentage of the population in gentrifying tracts experience depression. Although the relationships were insignificant, moderately gentrifying, intensely gentrifying, and displacement tracts were positively associated with the percent of the population experiencing depression. H1e and H1f, which predicted that gentrifying tracts have a higher percentage of the population experiencing frequent mental distress and a higher percentage of the population feeling socially isolated respectively, had similar results to H1d. In both cases, median age and the percent of the population with bachelor's degrees or higher were associated with a decrease in the percent of the population experiencing the adverse health outcome. No significant or defined relationship was found between gentrification and either frequent mental distress or feeling socially isolated.

H1g and H1h considered health behaviors, predicting that gentrifying tracts would have a higher percent of the population that binge drinks and higher percent of the population that has a short sleep duration during the night respectively. While the relationships from testing H1g were insignificant, the direction of this relationship aligned with what was predicted. Gentrifying and displacement tracts were all associated with an increase in the percent of the population that binge drinks. There was a weak, but significant, negative association between median age and binge drinking. The results from H1h did not support my prediction. Gentrifying tracts and were negatively associated with short sleep duration. Intensely gentrified tracts had a 2% decrease, significant at the 5% level, in the percent of the population with a short sleep duration.

Testing H1i, no strong or significant relationships were found between gentrification status and fair or poor self-rated health. Lastly, looking at a physical health outcome, coronary heart disease, H1j predicted that gentrifying tracts would have a greater percent of the population who experience this condition. However, the results do not support this. In fact, moderately gentrifying tracts and displacement tracts saw a .81% and .85% decrease respectively, both significant at the 5% level, in the percent of the population experiencing coronary heart disease.

Table 7: Effects of gentrification status on health outcomes and behaviors

Predictors	**CHD**	**Depression**	**Food insecurity**	**Lack of social and emotional support**	**Binge drinking**	**Short sleep duration**	**Fair or poor self-rated health**	**Routine doctor visits**	**Frequent mental distress**	**Socially isolated**
Controls for starting composition										
Median Age	.1558**** (3.86)	-.351**** (-4.87)	-.1125 (-.84)	-.2016*** (-2.80)	-.1867*** (-2.84)	-.1184*** (-2.74)	.0293 (.28)	.2924**** (5.44)	-.398**** (-5.41)	-.369**** (-4.91)
Percent white	-.1007 (-1.48)	-.0419 (-.37)	-.5938 (-1.66)	-.1814 (-1.34)	.1960 (1.39)	-.1853* (-1.70)	-.4578* (-1.94)	-.0066 (-.06)	-.1048 (-.57)	-.0163 (-.11)
Percent Black	-.0986 (-1.47)	-.1208 (-1.08)	-.4881 (-1.29)	-.1220 (-.88)	.1324 (.92)	-.0852 (-.77)	-.4093 (-1.67)	.0788 (.72)	-.1476 (-.82)	-.0348 (-.23)
Percent Asian	-.1408 (-1.68)	-.1301 (-1.02)	-.6523 (-1.56)	-.1391 (-.92)	.1933 (1.15)	-.1519 (-1.20)	-.5050* (-1.82)	-.0532 (-.43)	-.1620 (-.79)	-.0350 (-.20)
Percent Latino	-.1044 (-1.52)	-.0828 (-.77)	-.4467 (-1.21)	-.1342 (-.98)	.1841 (1.29)	-.1379 (-1.28)	-.3478 (-1.45)	-.0434 (-.41)	-.1371 (-.80)	-.0321 (-.22)
Educational attainment	-.0280* (-2.07)	-.0452* (-2.01)	-.2125** (-3.34)	-.094**** (-3.50)	.0340 (1.57)	-.083**** (-3.72)	-.155**** (-3.70)	.0050 (.35)	-.0971*** (-2.94)	-.0664** (-2.40)
Median household income	-.0001*** (-3.02)	-.0000 (-.70)	-.0001 (-.86)	-.0001 (-1.40)	.0001*** (2.71)	-.0000 (-1.10)	-.0001* (-1.76)	-.0000 (-1.45)	-.0001 (-1.16)	-.0000 (-.75)
Percent owner occupied	.0170 (1.13)	.0079 (.32)	-.0366 (-.59)	.0411 (1.22)	-.0304 (-1.14)	.0346 (1.52)	.0210 (.49)	.0385* (1.98)	.0303 (.87)	.0104 (.32)
Percent impoverished	-.0066 (-.39)	.0406 (1.59)	.1664*** (2.78)	.0165 (.30)	-.0384 (-1.47)	.0382* (1.93)	.0557 (1.43)	.0307 (.86)	.0534 (1.26)	.0266 (.50)
Gentrification status										
Weakly gentrified	-.3251	-1.5603	-3.0925*	-.6676	.6157	-1.0730	-1.8993	.0834	-2.2004**	-1.1764

	(-.68)	(-1.93)	(-1.31)	(-.59)	(.59)	(-1.31)	(-1.18)	(.12)	(-2.24)	(-1.12)
Moderately gentrified	-.8136** (-.215)	.4493 (.79)	-1.9900 (-1.23)	-.4315 (-.49)	.9050 (1.36)	-.1943 (-.34)	-1.4389 (-1.26)	-.6241 (-1.21)	.1906 (.30)	.2895 (.42)
Intensely gentrified	-.7608 (-.41)	2.3326 (1.39)	-8.0026** (-2.29)	-2.9699* (-1.89)	1.8717 (.62)	-2.0136** (-2.05)	-1.5726 (-.41)	-1.7358 (-.84)	1.1184 (.57)	-.9107 (-.37)
Displacement tract	-.8547* (-2.52)	1.1289* (1.73)	.9575* (.68)	.9060 (1.07)	.9060 (1.57)	.8116 (1.33)	.1898 (.21)	-1.0769** (-2.30)	1.7267 (1.87)	1.4937* (1.92)
Y-intercept	13.79 (1.87)	41.00** (3.39)	84.34** (2.12)	53.63**** (3.59)	4.65 (.31)	55.36**** (4.80)	65.96** (2.55)	66.39**** (5.47)	48.06** (2.50)	54.91*** (3.31)
R^2	.8398	.8074	.8711	.7634	.8320	.9010	.8724	.9053	.7818	.7569

Notes: Robust t-statistics in parentheses.

*P < .10 **P < .05 ***P < .01 ****P < .001

In sum, most of the models testing the relationship between gentrification status and health behaviors and health outcomes came back with weak and mostly insignificant results. Interestingly, all the statistically significant results showed a negative relationship between gentrification and adverse health outcomes. This runs contrary to my predictions and shows that the relationship is more nuanced. Another notable trend in these results is that while weakly, moderately, and intensely gentrified tracts were mostly negatively associated with the adverse health outcome or behavior, displacement tracts tended to a have a positive relationship with the adverse health outcome. Another interesting result relates to food insecurity. The relationship between intensely gentrified tracts was much stronger, in the negative direction, than that of weakly or moderately gentrified tracts. Additionally, the percent of the population living below the poverty line was positively associated with food insecurity. This suggests that as gentrification progresses, defined by median rent or home value in my case, a demographic shift occurs, with the proportion of wealthy residents increasing, thereby decreasing the prevalence of food insecurity.

As the percent of minority residents increases in gentrified tracts, there is an increasingly positive relationship between gentrification status and negative health behavior and outcomes.

Table 8 looks at the interaction between the percent of the population that are minorities and gentrification status, and how this interaction affects the relationship between gentrification and health outcomes and behaviors relative to non-gentrifying tracts. Hypotheses H2a through H2j are tested using these models. Using an interaction term between gentrification status and percent of the population that is minority status allows me to test how gentrification affects health outcomes independent of percent minority (without considering or interacting it), how the relationship between gentrification status and outcomes changes as the minority population changes, and what the effect of percent minority is in non-gentrifying tracts.

I tested the relationship between gentrification status, percent minority, and health risks / behaviors, which include feeling socially isolated, food insecurity, lack of social and emotional support, and short sleep duration. In this analysis it is interesting seeing the difference between the effect of gentrification status independent of percent minority compared to how the interaction changes the relationship. I found several significant results when testing the impact on the percentage of the population that feels socially isolated. In this case, independent of percent minority, weakly gentrified tracts saw an 11% decrease, significant at the 1% level, in the percent of people feeling socially isolated, and intensely gentrified tracts saw a 20% decrease, also significant at the 1% level, in the percent of people feeling socially isolated. In non-gentrifying tracts, a 1% increase in the percent of minority residents was associated with a .1% increase in the percent of people feeling socially isolated; this relationship was weak but significant at the 1% level. Looking at the interaction between percent minority and gentrification status, I found that in weakly gentrified tracts a 1% increase in the percent of minority residents was associated with a .1% increase, significant at the 5% level, in the percent of the population feeling socially isolated. Additionally, a 1% increase in the percentage of minority residents living in intensely gentrified tracts was associated with a .4% increase, significant at the 1% level, in the percent of the population experiencing social isolation. These results show a strong interaction between percent minority and gentrification status. While gentrification independent of percent minority showed a negative relationship to the percent of the population feeling socially isolated (meaning the percent experiencing this health risk decreases), the interaction showed that as the percentage of minority residents increases in gentrifying areas, the percent of people feeling socially isolated also increases.

No significant results were found for the relationship between gentrification status and lack of social or emotional support. Although I did not find statistically significant results between gentrification or the interaction between percentage minority and gentrification on this health risk, in non-gentrifying tracts a 1% increase in the percent of minority residents was associated with .2% increase, significant at the .1% level, in the percent of the population experiencing a lack of social or emotional support. This shows a weak but significant relationship.

The results from my model looking at food insecurity showed that intensely gentrifying tracts were associated with a 30% increase, significant at the 5% level, in the percent of the population experiencing food insecurity. Additionally, for every 1% increase in the percent of the population living below the poverty line, and for every 1% increase in the percent of minority residents, there is a .2% increase in the percent of people experiencing food insecurity for both, both statistically significant at the 5% level. Contrary to the overall positive relationship between percent minority and food insecurity, the interaction between intensely gentrified areas and percent minority is both negative and statistically significant. In intensely gentrified areas, the percent of people experiencing food insecurity decreases by .8% for every 1% increase in the percent of minority residents. Food insecurity decrease by 0.2% for every 1% increase in the percent of people with a bachelor's degree or higher, significant at the 1% level. Overall, higher minority populations and poverty rates are associated with increased food insecurity. However, higher educational attainment tends to reduce it.

No significance was found between gentrification and short sleep duration or the interaction between percent minority and gentrification on short sleep duration. While I did not find statistically significance in these relationships, a 1% increase in the percent of minority residents living in a non-gentrifying tract was associated with a .1% increase, significant at the 1% level, in the percent of the population experiencing a short sleep duration. This represents a very weak but significant positive relationship between percent minority and short sleep duration.

I also looked at how gentrification and the percentage minority impact health behaviors such as going for routine doctor visits and binge drinking. The percent of the population that goes for routine doctors' visits was positively associated with median age. For every year increase in median age there was a .3% increase, significant at the .1% level, in the percent of people going for routine doctors' visits. Additionally, intensely gentrified areas had a strong positive association with doctors' visits. Intensely gentrified tracts, independent of percent minority, had a 19.6% increase, significant at the .1% level, in the percent of people going for routine doctors' visits. However, in these same intensely gentrified tracts, as the percent of minority residents increases, the percent of people going for these doctors' visits decreases. A 1% increase in the percent of residents in an intensely gentrified area was associated with a .5% decrease, significant at the .1% level, in the percent of people going for routine doctors' visits. Also interestingly, there was a weak but positive and significant relationship between the percent of the population that is Black, non-Hispanic, and the percent of the population going for routine doctors' visits. Binge drinking was negatively associated with an increase in median age and had a strong negative relationship with intensely gentrified tracts. Intensely gentrified tracts independent of percent minority had a 29% decrease in the percent of people binge drinking, significant at the .1% level. The results from the interaction term supported my hypothesis that the negative effects of gentrification on health would be worse based on minority status. A 1% increase in the percent of minority residents living in an intensely gentrified tracts was associated with a .7% increase, significant at the .1%, in the percent of people binge drinking.

The physical and mental health outcomes that I considered included coronary heart disease, frequent mental distress, and depression. Intensely gentrified tracts independent of percent minority had a 19% increase, significant at the .1% level, in the percent of people with coronary heart disease. The results from my interaction term did not support my prediction that the effect of gentrification on negative health outcomes would be worse for minority residents. A 1% increase in the percent of minority residents living in an intensely gentrified tract was associated with a .5% decrease, significant at the .1% level, in the percent of people with coronary heart disease. For frequent mental distress, there was a weak but negative and significant relationship with median age. Additionally, frequent mental distress had a weak positive relationship with the percent of people living below the poverty line. The results from my model support my hypothesis, with the effects of gentrification on frequent mental distress being worse as the percent of minority residents increase. Weakly gentrified tracts independent of percent minority were associated with a 12.5% decrease, significant at the 1% level, in the percent of the population experiencing frequent mental distress. Intensely gentrified tracts with independent of percent minority were associated with a 18.9% decrease, significant at the 5% level, in the percent of the population experiencing frequent mental distress. While both these relationships show a decrease in the percent of the population experiencing frequent mental distress the results change in relation to the percent of the population that is a minority. A 1% increase in the percent of minority residents living in a weakly gentrified tracts was associated with a .14% increase, significant at the 5% level, in the percent of people experiencing frequent mental distress. Additionally, a 1% increase in the percent of minority residents living in an intensely gentrified tract was associated with a .4% increase, significant at the 5% level, in the percent of people experiencing frequent mental distress. While both impacts are smaller, it represents a larger issue here. The effect of gentrification, independent of race, on adverse health outcomes is negative, fewer people experiencing the negative outcome, but positive as the percent of minority residents increases. The results from testing the impact of gentrification status and percent minority on depression show similar results, supporting my hypothesis that the impact of gentrification is more harmful to the health of minority residents. Weakly gentrified tracts independent of percent minority had a 10.6% decrease, significant at the 1% level, in the percent of people experiencing depression. Intensely gentrified tracts independent of percent minority had a 16% decrease, significant at the 1% level, in the percent of people experiencing depression. Weakly and intensely gentrified tracts both had a positive relationship with the percentage of people experiencing depression as the percent of minority residents increased. A 1% increase in the percent of minority residents living in weakly gentrified tracts was associated with a .1% increase in the percent of people experiencing depression, significant at the 5% level. A 1% increase in the percent of minority residents living in an intensely gentrified tracts had a .4% increase, significant at the 1% level, in the percent of residents experiencing depression.

The results from looking at fair or poor self-rated health did not support my hypothesized relationship between gentrification and percent minority. Intensely gentrified areas independent of percent minority were associated with a 37% increase, significant at the 1% level, in the percent of residents reporting fair or poor health. However, a 1% increase in the percent of

Table 8: Interaction between percent minority and gentrification status on health outcomes and behaviors

Predictors	CHD	Depression	Food insecurity	Lack of social and emotional support	Binge drinking	Short sleep duration	Fair or poor self-rated health	Routine doctor visits	Frequent mental distress	Socially isolated
Controls for starting composition										
Median Age	0.19**** (5.61)	-0.31**** (-4.54)	0.072 (0.56)	0.0587 (-1.00)	-.26**** (-4.40)	-0.0399 (-0.74)	0.1347 (1.19)	.31**** (5.20)	-.41**** (-4.29)	-.33**** (-5.12)
Percent white	-0.034 (-0.76)	-0.111 (-0.79)	-0.224 (-0.70)	-0.0869 (-0.79)	0.0206 (0.21)	-0.0852 (-0.81)	-0.1800 (-1.03)	0.0306 (0.37)	-0.1289 (-0.60)	-0.0342 (-0.26)
Percent Black	-0.014 (-0.31)	-0.186 (-1.44)	-0.223 (-0.65)	-0.1298 (-1.21)	-0.0406 (-0.42)	-0.0396 (-0.38)	-0.1523 (-0.84)	0.154** (2.04)	-0.2061 (-1.02)	-0.1320 (-1.07)
Percent Asian	-0.008 (-0.15)	-0.249 (-1.64)	-0.232 (-0.60)	-0.1151 (-0.92)	-0.0667 (-0.61)	-0.0731 (-0.59)	-0.1274 (-0.62)	0.0700 (0.81)	-0.2703 (-1.14)	-0.1703 (-1.18)
Percent Latino	-0.016 (-0.36)	-0.166 (-1.28)	-0.162 (-0.48)	-0.1281 (-1.15)	0.0041 (0.05)	-0.0818 (-0.80)	-0.0869 (-0.49)	0.0386 (0.52)	-0.2126 (-1.05)	-0.1304 (-1.02)
Educational attainment	-0.046*** (-3.32)	-0.043 (-1.25)	-0.198*** (-3.00)	-.0547** (-2.10)	.0441* (1.88)	-.0573** (-2.27)	-.17**** (-3.65)	-0.0224 (-1.08)	-0.0757 (-1.61)	-0.0275 (-0.92)
Median household income	-.0001*** (-3.20)	-0.00003 (-0.74)	-0.00002 (-0.29)	-0.00005 (-1.32)	0.0001 (2.18)	-0.0000 (-0.79)	-0.0001 (-1.21)	-0.0000 (-1.59)	-0.0001 (-1.13)	-0.00003 (-0.76)

Percent owner occupied	0.002 (0.16)	0.026 (0.82)	-0.080 (-1.31)	0.0203 (0.66)	-0.0141 (-0.58)	0.0289 (1.30)	0.0005 (0.01)	0.0207 (1.00)	0.0502 (1.11)	0.0144 (0.45)
Percent impoverished	-0.021 (-1.65)	.056** (2.18)	0.18** (2.68)	0.0373 (0.76)	-0.0303 (-1.38)	.050** (2.22)	0.0562 (1.19)	0.0063 (0.26)	.0835** (2.07)	0.0585 (1.41)
Gentrification status										
Weakly gentrified	1.978 (1.03)	-10.62*** (-2.92)	-13.435 (-1.57)	-5.5205 (-1.10)	-4.5532 (-0.79)	1.6530 (0.56)	-2.0443 (-0.30)	5.1146 (1.10)	-12.54** (-2.83)	-11.47*** (-2.90)
Moderately gentrified	-0.612 (-0.44)	-1.084 (-0.57)	4.301 (0.97)	0.8751 (0.39)	1.2811 (0.70)	-0.0441 (-0.02)	-1.1847 (-0.29)	0.2342 (0.13)	-1.9473 (-0.77)	1.0691 (0.54)
Intensely gentrified	19.51**** (7.02)	-16.44*** (-3.30)	30.62** (2.40)	4.5631 (0.62)	-29.0**** (-6.81)	5.2580 (1.01)	37.18*** (3.42)	19.6**** (4.72)	-18.863** (-2.54)	-20.15*** (-3.04)
Displacement tract	-0.671 (-0.62)	-0.598 (-0.30)	1.613 (0.43)	3.8256 (1.56)	1.8854 (1.13)	1.2461 (0.66)	-2.0683 (-0.68)	-0.2776 (-0.17)	-0.2414 (-0.09)	2.6773 (1.12)
Non-gentrified	-0.028* (-1.73)	-0.024 (-0.52)	.178** (2.36)	0.177**** (5.01)	-0.0002 (-0.01)	.0927*** (3.11)	0.0208 (0.33)	-0.0538 (-1.34)	0.0341 (0.57)	0.129*** (3.35)
Gentrification status # percent minority										
Weakly gentrified	-0.033 (-1.39)	.129** (2.52)	0.119 (0.97)	0.0502 (0.73)	0.0716 (1.00)	-0.0423 (-1.02)	-0.0009 (-0.01)	-0.0698 (-1.20)	0.144** (2.28)	0.132** (2.45)

Moderately gentrified	-0.008 (-0.35)	0.030 (0.94)	-0.110 (-1.32)	-0.0225 (-0.58)	-0.0017 (-0.06)	-0.0023 (-0.08)	-0.0091 (-0.13)	-0.0197 (-0.72)	0.0413 (0.92)	-0.0086 (-0.25)
Intensely gentrified	-0.45**** (-7.11)	.402*** (3.34)	-0.825*** (-2.81)	-0.1310 (-0.77)	.674*** (6.79)	-0.1405 (-1.15)	-0.847** (-3.43)	-.474*** (-4.77)	0.4394* (2.48)	.441*** (2.83)
Displacement tract	0.005 (0.30)	0.023 (0.82)	-0.010 (-0.17)	-0.0619 (-1.54)	-0.0244 (-.98)	-0.0127 (-0.48)	0.0463 (0.97)	-0.0019 (-0.08)	0.02909 (0.50)	-0.0364 (-0.95)
Y-intercept	7.718 (1.39)	50.84*** (3.00)	34.051 (0.96)	32.348** (2.59)	24.5416* (2.30)	38.442** (3.34)	34.0944 (1.62)	64.99*** (5.80)	49.4184 (1.99)	49.80*** (3.22)
R^2	.9265	.8465	.9032	.8535	.9108	.9228	.9085	.9423	.8165	.8627

Notes: Robust t-statistics in parentheses.

*P < .10 **P < .05 ***P < .01 ****P < .001

minority residents living in intensely gentrified tracts was associated with a .8% decrease, significant at the 1% level, in the percent of people reporting fair or poor health.

Overall, the results on the interaction between gentrification status and percent minority supported my prediction that as the percent of minority residents increase the effect of gentrification on health outcomes becomes worse, ie. a greater percentage of the population experiencing a health risk or negative health outcome. In most of the models, gentrification seemingly improved health outcomes and behaviors/risks. However, this was the case when gentrification status is looked at independent of percent minority. As the percent of minority residents increased in the gentrified areas, a higher percentage of the population was predicted to experience the negative health outcome.

As the percent of Black residents increases in gentrified tracts, there is an increasingly positive relationship between gentrification status and negative health behavior and outcomes.

Table 9 includes the results from my models that test the interaction between percent Black and gentrification status on health relative to non-gentrifying tracts. Unsurprisingly, the results here are very similar to those from the interaction between percent minority and gentrification status on health. Gentrification status, independent of percent Black, generally leads to improved health behaviors and outcomes. As the percent of Black residents increases in gentrified tracts, this relationship flips and the increase in the percent of Black residents is associated with an increase in negative health behaviors and outcomes.

Independent of percent Black, intensely gentrified tracts were associated with a 10.4 percent decrease, significant at the 1% level, in the percent of the population that feels socially isolated. However, when looking at the interaction between percent Black and gentrification we find that a 1% increase in the percentage of the population that is Black is associated with a 1.4% increase, significant at the 5% level, in the percent of the population experiencing social isolation.

Depression also decreases in gentrified tracts, independent of percent Black. There was a 6.2% decrease, significant at eh 1% level, in the percent of the population experiencing depression. The interaction between percent Black and gentrification status once again tells a different story. As the percent of the population that is Black increases in gentrified tracts, a greater percent of the population reports experiencing depression. A 1% increase in the percent of the population that is Black was associated with a 1.22% increase, significant at the .1% level, in the percent of the population experiencing depression.

Binge drinking shows this same trend; decreasing in relation to gentrification status independent of percent Black, but increasing as the percent of the population that is Black increases. The percent of the population going for routine doctor checkups increase in relation to gentrification status independent of percent Black, but then decreases as the percent of the population that is Black increases.

In all these cases we are seeing that there are health benefits associated with gentrification when looked at independently of race. However, these results demonstrate that these benefits do not exist equally across racial lines. An increase in the percent of Black residents living in intensely gentrified tracts leads to worse health. This may be partly explained by breakdown in social cohesion and physical and economic changes. As shown in table 5, more maturely gentrified tracts see a large decrease in the percent of their population that is Black or minority. This decrease could cause the breakdown of social networks which are important for preventing social isolation, depression, and negative health behaviors. Because of the changes associated with gentrification, Black and minority residents that remain in intensely gentrified tracts experience worse health outcomes.

Table 9: Interaction between percent Black and gentrification status on health outcomes and behaviors

Predictors	**CHD**	**Depression**	**Food insecurity**	**Lack of social and emotional support**	**Binge drinking**	**Short sleep duration**	**Fair or poor self-rated health**	**Routine doctor visits**	**Frequent mental distress**	**Socially isolated**
Controls for starting composition										
Median Age	.22**** (5.06)	-.31**** (-5.01)	0.0560 (0.32)	-0.1361 (-1.45)	-.3**** (-5.44)	-0.0774 (-1.25)	0.1811 (1.44)	.4**** (6.79)	-.4**** (-4.53)	-.4**** (-4.22)
Percent white	-0.0223 (-0.47)	-0.1085 (-0.85)	-0.5401 (-1.45)	-0.214* (-1.87)	0.0443 (0.42)	-0.1647 (-1.42)	-0.3280 (-1.53)	0.1072 (1.23)	-0.1853 (-0.91)	-0.1385 (-1.04)
Percent Black	-0.0181 (-0.38)	-0.1513 (-1.08)	-0.3832 (-1.03)	-0.1734 (-1.32)	0.0240 (0.22)	-0.0927 (-0.71)	-0.2296 (-1.07)	0.1405 (1.40)	-0.1915 (-0.83)	-0.1371 (-0.89)
Percent Asian	-0.0114 (-0.20)	-0.2268 (-1.52)	-0.5055 (-1.15)	-0.1644 (-1.18)	-0.0360 (-0.30)	-0.1162 (-0.84)	-0.2606 (-1.02)	0.1060 (1.01)	-0.2704 (-1.13)	-0.2051 (-1.29)
Percent Latino	-0.0214 (-0.45)	-0.1469 (-1.21)	-0.3753 (-1.00)	-0.1691 (-1.46)	0.0240 (0.24)	-0.1178 (-1.04)	-0.2014 (-0.94)	0.0766 (0.89)	-0.2143 (-1.12)	-0.1569 (-1.22)
Educational attainment	-.037*** (-3.38)	-0.0356 (-1.40)	-.223*** (-3.30)	-.097*** (-3.23)	.046** (2.26)	-.09*** (-3.44)	-.2**** (-4.34)	-0.0013 (-0.08)	-.086** (-2.27)	-0.057* (-1.98)
Median household income	-0.00*** (-2.90)	-0.00003 (-0.70)	-0.00007 (-1.02)	-0.0001 (-1.44)	.0001** (2.63)	-0.0000 (-1.04)	-.0001* (-1.73)	-0.0000 (-1.44)	-0.0001 (-1.12)	-0.00004 (-0.84)

Percent owner occupied	-0.0023 (-0.21)	0.0206 (0.75)	-0.0954 (-1.33)	0.0187 (0.52)	-0.0039 (-0.16)	0.0243 (0.88)	-0.0297 (-0.70)	0.0264 (1.22)	0.0379 (0.91)	0.0159 (0.45)
Percent impoverished	-0.0211 (-1.33)	0.0313 (1.04)	0.1088 (1.48)	0.0207 (0.36)	-0.0256 (-1.00)	0.0431 (1.64)	0.0002 (0.00)	0.0283 (0.97)	0.0415 (0.86)	0.0310 (0.57)
Gentrification status										
Weakly gentrified	-0.90** (-2.08)	-2.2094 (-1.61)	-3.6341 (-1.15)	1.2936 (0.95)	1.5901 (1.54)	-0.4763 (-0.41)	-3.62** (-2.13)	-0.7395 (-0.74)	-2.5993 (-1.46)	0.0320 (0.02)
Moderately gentrified	-0.96** (-2.29)	0.5578 (0.70)	-1.1021 (-0.60)	0.6800 (0.62)	1.47** (2.07)	0.1671 (0.20)	-1.3308 (-1.16)	-1.32** (-2.27)	0.6839 (0.70)	1.2174 (1.32)
Intensely gentrified	9.2**** (7.55)	-6.24*** (-3.24)	9.1926 (1.55)	1.5306 (0.43)	-15.**** (-8.73)	2.6335 (1.24)	18.5*** * (4.15)	9**** (4.52)	-6.96** (-2.55)	-10.4*** (-3.23)
Displacement tract	-0.3745 (-0.76)	0.9394 (0.92)	3.8098 (1.40)	2.2185 (1.62)	0.4487 (0.49)	1.1271 (1.06)	2.0157 (1.17)	-1.0695 (-1.60)	1.8535 (1.19)	2.0033 (1.54)
Non-gentrified	0.0003 (0.01)	-0.0413 (-0.82)	-0.0185 (-0.19)	0.0475 (0.67)	-0.0483 (-1.53)	0.0396 (0.80)	-0.0377 (-0.52)	0.0531 (1.25)	-0.0339 (-0.48)	-0.0062 (-0.10)
Gentrification status # percent black										
Weakly gentrified	0.0299 (1.37)	0.0689 (0.94)	0.0559 (0.37)	-0.1346 (-1.65)	-0.0406 (-0.82)	-0.0469 (-1.01)	0.1231 (1.63)	0.0321 (0.54)	0.0583 (0.58)	-0.0581 (-0.64)

Moderately gentrified	-0.0077 (-0.62)	0.0014 (0.06)	-0.0813 (-1.48)	-0.0632 (-1.92)	-0.0052 (-0.30)	-0.0251 (-0.94)	-0.0435 (-1.07)	0.0222 (1.08)	-0.0213 (-0.59)	-0.0371 (-1.13)
Intensely gentrified	-1.5**** (-7.12)	1.2**** (3.60)	-2.56** (-2.50)	-0.6304 (-0.99)	2.4*** * (9.14)	-0.647* (-1.80)	-3**** (-4.02)	-2**** (-4.31)	1.15** (2.18)	1.38** (2.27)
Displacement tract	-0.0074 (-0.56)	0.0092 (0.38)	-0.0909 (-1.11)	-0.0617 (-1.21)	0.0079 (0.32)	-0.0160 (-0.59)	-0.0396 (-0.90)	0.0019 (0.09)	-0.0041 (-0.11)	-0.0315 (-0.73)
Y-intercept	4.5241 (0.79)	49.2**** (3.61)	75.366* (1.83)	55**** (4.12)	22.6** (2.11)	52**** (4.24)	49.98** (2.09)	53**** (5.27)	57.20** (2.69)	68**** (4.54)
R^2	.9179	.8358	.8887	.7975	.9128	.9065	.9130	.9384	.7991	.7972

Notes: Robust t-statistics in parentheses.

*P < .10 **P < .05 ***P < .01 ****P < .001

CONCLUSION

The results from testing the effect of gentrification status on percent minority and percent Black support my prediction that more intensely gentrified tracts are associated with a decrease in the percent of the population that are minorities and the percent of the population that is Black relative to non-gentrifying tracts. Although not significant at the 5% level, the direction and strength of the relationship shows that weakly gentrified tracts are associated with an increase in the percent minority relative to non-gentrifying tracts while more intensely gentrified tracts are associated with a decrease in the percent of minority residents. Additionally, displacement tracts were positively associated with percent minority and with percent Black. This demonstrates that as gentrification progesses in areas, minority residents are forced out.

Overall, the results from table 7 did not support my predictions. While I predicted that gentrification status would be associated with a higher percent of the population that experience adverse health behaviors and health outcomes relative to non-gentrifying tracts, the statistically significant results showed the opposite. Although weakly, moderately, and intensely gentrified tracts were negatively associated with adverse health outcomes, displacement tracts had a positive relationship with most negative health outcomes and behaviors.

The results in table 8, which looked at how the interaction between percent minority and gentrification status impact health outcomes and behaviors, provided me with more significant results and helped shed light on the nuance in the relationship between gentrification and health. Here, I found support for my predictions that the effect of gentrification on health is variable based on race. In most of these models, the association between gentrification and health when independent of percent minority is negative. These results align with those from table 7; weakly, moderately, and intensely gentrified tracts had a lower percent of the population experiencing negative health outcomes and behaviors relative to non-gentrifying tracts. However, the results from table 8 and these models became more telling once I looked at the interaction between gentrification status and percent minority. In most of the models, increasing the percent of minority residents in a gentrified tract was associated with an increase in the percent of people experiencing a negative health outcome or behavior relative to non-gentrifying tracts. This demonstrates that gentrification independent of minority residents is correlated with health benefits, but when gentrification occurs around more minority residents it becomes associated with health detriments. The results from the interaction between percent Black and gentrification status showed a very similar trend. Gentrification independent of the percent of Black residents had a negative relationship to adverse health behaviors and outcomes, but then in the presence of Black residence this effect flips, and the relationship is positive. This relationship is stronger in more intensely gentrified tracts where more significant displacement and changes to the neighbourhood environment have occurred.

DISCUSSION

Findings

With my study, I aimed to understand the effect of gentrification on health and how race plays a role in this effect. Furthermore, I wanted to understand how displacement, caused by gentrification, impacts health. From my research, I predicted that gentrification would negatively affect the health of residents, with the effects being worse and larger for minority residents. Additionally, I predicted that the effects of gentrification on health would be more severe in displacement tracts compared to gentrifying tracts. The models that I ran tested the relationship between gentrification status and health outcomes, as well as the interaction between race and gentrification status, and the effect of gentrification status on racial demographics. I categorized gentrifiable tracts as non-gentrified, weakly gentrified, moderately gentrified, intensely gentrified, or displacement tracts. The health outcomes and behaviors/risks that I included were coronary heart disease, depression, food insecurity, lack of social and emotional support, binge drinking, short sleep duration, fair or poor self-rated health, routine doctor visits, frequent mental distress, and feeling socially isolated. My findings showed that gentrified tracts were associated with a decrease in the percent of the population who experience depression, frequent mental distress, social isolation, and binge drinking, and an increase in routine doctors' visits, all relative to non-gentrifying tracts. This relationship is stronger for more intensely gentrified tracts and has greater statistical significance and strength when looking at gentrification status independent of the percent of minority or Black residents. While this is not the relationship that I expected, once I introduced race as an interaction term, I found that as the percent of minority and percent of Black residents increases the effect of gentrification status on health becomes harmful. These findings are illuminating in that they provide more insight on the nuance of how gentrification impacts health. Previous research had not used a quantitative dataset to measure the impact of gentrification on health at the census tract level. Much of the research aimed to understand the experience of residents through focus group discussion, and research that did use a more quantitative approach looked at gentrification's impact on different consequences. From this research, it is understood that gentrification causes feelings of social exclusions, cultural displacement, and financial insecurity. My research allowed me to test how the changes associated with gentrification impact the health of residents. Many articles claim that there are both positive and negative effects of gentrification, and my findings help us understand how the benefits and harms from gentrification are distributed. Gentrification was largely beneficial to residents' health when looked at independently of percent minority; however, increasing the percent of minority residents caused the impact of gentrification on health to deteriorate. As the percent of minority residents increases in a gentrifying tract, so too does the percent of the population experience adverse health outcomes and behaviors/risks. This demonstrates how gentrifications' impact on health is contingent on the race of residents.

Understanding how gentrification impacts health, and how this impact changes based on the racial composition of gentrifying areas can guide policy makers in their decisions to protect the health and well-being of more vulnerable residents. It sheds light on when one might expect the impacts of gentrification to be more harmful and can help community health initiatives to focus their efforts on the areas that need the most support.

Limitations

My main limitations relate to the availability of health outcome information at the census tract level, and the number of usable observations that I ended up with for my study. The PLACES: Local data for better health data release provides the best available tract level health information. This dataset uses BRFSS (individual-level data gathered from the BRFSS survey) to generate regression models which predict whether someone has depression, coronary heart disease, etc. These models are based on a social determinant of health framework and use age, sex, race, income, and other demographic characteristics to predict the prevalence of behaviors and diseases at the aggregate level. Therefore, the statistics that this dataset provides are not as accurate as a raw count of prevalence in the population would be. Additionally, since I construct my variable for gentrification status using some similar demographic characteristics, I needed to control for a tracts' composition at the starting point and used 2008-2012 demographic aggregates to do so. Since the PLACES dataset included different survey questions from year to year, I had a difficult time collecting year to year data on health outcomes. Because of this, I had to look at health outcomes statically, meaning how does the gentrification status of a census tract impact the health outcomes in 2022. Gentrification is a highly dynamic process, so some of the nuance is lost when looking at it as a static variable and comparing that against health outcomes in a singular point in time. Since I was combining data from different sources, I ran into some issues with census tract boundaries which caused me to lose many usable observations. The discrepancies between tracts in these different datasets led me to only have 50 usable observations, out of the 114 gentrifiable tracts I would hope to have complete data for. This is obviously a much smaller subset than I was hoping for, but given the inconsistencies in the data this was the best that I could do under my time constraint. Therefore, my findings represent correlations that are true for the subset of Suffolk County, MA, that I looked at, but may not hold true under other contexts.

Future research

Future research should focus on using longitudinal data, that measures the impact of gentrification on health at the individual level. This will help illuminate how gentrification as a dynamic process affects the health of residents over time. Furthermore, future research should question and test whether my findings hold true in other cities. Gentrification is highly contextual, so better understanding how its effects vary between cities will enable more effective policy response in mediating its potential harms. Using a broader dataset, ie. including all census tracts in the U.S. would be interesting to see what high-level / broad association exists between gentrification and health.

References

Rucks-Ahidiana, Z. (2022). Theorizing Gentrification as a Process of Racial Capitalism. City & Community, 21(3), 173-192. https://doi.org/10.1177/15356841211054790

Dreier, P. (2023, March 10). *Who benefits from gentrification?*. PBS SoCal. https://www.pbssocal.org/shows/city-rising/who-benefits-from-gentrification

Mitchell, B. (2024, July 23). *Decades of disinvestment: Historic redlining and mortgage lending since 1981 " Ncrc*. NCRC. https://ncrc.org/decades-of-disinvestment/

MacKenzie, B. (2021, January 20). *Mapping disinvestment & displacement: A conversation with dr. Brittany Lewis*. Twin cities habitat for humanity. https://www.tchabitat.org/blog/disinvestment-and-displacement

Phillip J. Obermiller & Thomas E. Wagner. (2022, November 15). *Meeting the challenge of municipal disinvestment*. progressive city. https://www.progressivecity.net/single-post/meeting-the-challenge-of-municipal-disinvestment

Meier, H. (n.d.). *Mapping inequality*. Digital Scholarship Lab. https://dsl.richmond.edu/panorama/redlining/health

Cole, H. V. S., Mehdipanah, R., Gullón, P., & Triguero-Mas, M. (2021). Breaking Down and Building Up: Gentrification, Its drivers, and Urban Health Inequality. *Current environmental health reports*, *8*(2), 157–166. https://doi.org/10.1007/s40572-021-00309-5

Munneke, H. J., & Womack, K. S. (2015). Neighborhood renewal: The decision to renovate or tear down. *Regional Science and Urban Economics*, *54*, 99–115. https://doi.org/10.1016/j.regsciurbeco.2015.08.001

Tulier, M. E., Reid, C., Mujahid, M. S., & Allen, A. M. (2019). "Clear action requires clear thinking": A systematic review of gentrification and health research in the United States. *Health & place*, *59*, 102173. https://doi.org/10.1016/j.healthplace.2019.102173

Smith, G. S., Breakstone, H., Dean, L. T., & Thorpe, R. J., Jr (2020). Impacts of Gentrification on Health in the US: a Systematic Review of the Literature. *Journal of urban health : bulletin of the New York Academy of Medicine*, *97*(6), 845–856. https://doi.org/10.1007/s11524-020-00448-4

Wolfe, R. (2024, July 20). *Why Americans aren't having babies*. Wall Street Journal. https://www.wsj.com/lifestyle/relationships/americans-babies-childless-birthrate-daf438f9

Bladen, J., & Mateyka, P. (2023, September 5). *50 years of PD&R's gentrification research*. 50 Years of PD&R's Gentrification Research | Howard University COAS Centers. https://coascenters.howard.edu/50-years-pdrs-gentrification-research

Bhavsar, N. A., Yang, L. Z., Phelan, M., Shepherd-Banigan, M., Goldstein, B. A., Peskoe, S., Palta, P., Hirsch, J. A., Mitchell, N. S., Hirsch, A. G., Lunyera, J., Mohottige, D., Diamantidis, C. J., Maciejewski, M. L., & Boulware, L. E. (2022). Association between Gentrification and Health and Healthcare Utilization. *Journal of urban health : bulletin of the New York Academy of Medicine*, *99*(6), 984–997. https://doi.org/10.1007/s11524-022-00692-w

Cole, H. V. S., Triguero-Mas, M., Connolly, J. J. T., & Anguelovski, I. (2019). Determining the health benefits of green space: Does gentrification matter? *Health & Place*, *57*, 1–11. https://doi.org/10.1016/j.healthplace.2019.02.001

Breyer, B., & Voss-Andreae, A. (2013). Food mirages: Geographic and economic barriers to healthful food access in Portland, Oregon. *Health & Place*, *24*, 131–139. https://doi.org/10.1016/j.healthplace.2013.07.008

Whittle, H. J., Palar, K., Hufstedler, L. L., Seligman, H. K., Frongillo, E. A., & Weiser, S. D. (2015). Food insecurity, chronic illness, and gentrification in the San Francisco Bay Area: An example of structural violence in united states public policy. *Social Science & Medicine*, *143*, 154–161. https://doi.org/10.1016/j.socscimed.2015.08.027

Cole, H. V. S., & Franzosa, E. (2022). Title: advancing urban health equity in the United States in an age of health care gentrification: a framework and research agenda. *International journal for equity in health*, *21*(1), 66. https://doi.org/10.1186/s12939-022-01669-6

Parry, B. (2014, January 9). *St. John's hospital building sold to apartment developer*. QNS. https://qns.com/2014/01/st-johns-hospital-building-sold-to-apartment-developer/#:~:text=A%20consortium%20of%20Asia%2Dbased,at%2090%2D02%20Queens%20Blvd.

Ellwardt, L., Wittek, R. P. M., Hawkley, L. C., & Cacioppo, J. T. (2020). Social Network Characteristics and Their Associations With Stress in Older Adults: Closure and Balance in a Population-Based Sample. *The journals of gerontology. Series B, Psychological sciences and social sciences*, *75*(7), 1573–1584. https://doi.org/10.1093/geronb/gbz035

Versey, H. S. (2018). A tale of two Harlems: Gentrification, social capital, and implications for aging in place. *Social Science & Medicine*, *214*, 1–11. https://doi.org/10.1016/j.socscimed.2018.07.024

Foong, H. F., Ibrahim, R., Hamid, T. A., & Haron, S. A. (2021). Social networks moderate the association between physical fitness and cognitive function among community-dwelling older adults: A population-based study. *BMC Geriatrics*, *21*(1). https://doi.org/10.1186/s12877-021-02617-9

Braren, S. (2023, November 7). *Social Connection and physical health*. Social Creatures. https://www.thesocialcreatures.org/thecreaturetimes/social-connection-physical-health

Ellwardt, L., Wittek, R. P. M., Hawkley, L. C., & Cacioppo, J. T. (2020). Social Network Characteristics and Their Associations With Stress in Older Adults: Closure and Balance in a Population-Based Sample. *The journals of gerontology. Series B, Psychological sciences and social sciences*, *75*(7), 1573–1584. https://doi.org/10.1093/geronb/gbz035

Shmool, J. L., Yonas, M. A., Newman, O. D., Kubzansky, L. D., Joseph, E., Parks, A., Callaway, C., Chubb, L. G., Shepard, P., & Clougherty, J. E. (2015). Identifying Perceived Neighborhood Stressors Across Diverse Communities in New York City. *American journal of community psychology*, *56*(1-2), 145–155. https://doi.org/10.1007/s10464-015-9736-9

Hannah, S., & Jiang, K. (2021, May 26). *From redlining to gentrification: The policy of the past that affects health outcomes today*. From Redlining to Gentrification: The Policy of the Past that Affects Health Outcomes Today. https://info.primarycare.hms.harvard.edu/perspectives/articles/redlining-gentrification-health-outcomes

McLeod, M. N., Heller, D., Manze, M. G., & Echeverria, S. E. (2019). Police interactions and the mental health of Black Americans: A systematic review. *Journal of Racial and Ethnic Health Disparities*, *7*(1), 10–27. https://doi.org/10.1007/s40615-019-00629-1

Almeida, D. M. (2024). The time is now for integrative Multilayered Stress Research and Mitigation. *Frontiers in Science, 2*. https://doi.org/10.3389/fsci.2024.1389481

Franco, J., Mitchell, B., & Richardson, J. (2022, November 2). *Shifting neighborhoods: Gentrification and cultural displacement in American cities " NCRC*. NCRC. https://ncrc.org/gentrification/

Delong S. (2023). Urban health inequality in shifting environment: systematic review on the impact of gentrification on residents' health. *Frontiers in public health*, *11*, 1154515. https://doi.org/10.3389/fpubh.2023.1154515

Ncrc. (2021, March 11). *The Daily Free Press: Boston remains highly gentrified despite housing efforts " NCRC*. NCRC. https://ncrc.org/the-daily-free-press-boston-remains-highly-gentrified-despite-housing-efforts/

Mercado, M. (2021, February 18). *Boston remains highly gentrified despite housing efforts*. The Daily Free Press. https://dailyfreepress.com/2021/02/18/boston-remains-highly-gentrified-despite-housing-efforts/

Ding, L., Hwang, J., & Divringi, E. (2016). Gentrification and residential mobility in Philadelphia. *Regional Science and Urban Economics*, *61*, 38–51. https://doi.org/10.1016/j.regsciurbeco.2016.09.004

Lim, S., Chan, P. Y., Walters, S., Culp, G., Huynh, M., & Gould, L. H. (2017). Impact of residential displacement on healthcare access and mental health among original residents of gentrifying neighborhoods in New York City. *PloS one*, *12*(12), e0190139. https://doi.org/10.1371/journal.pone.0190139

Herman, A. (2019, January). *Mapping over two decades of neighborhood change in the* ... Joint Center for Housing Studies of Harvard University. https://www.jchs.harvard.edu/sites/default/files/Harvard_JCHS_mapping_neighborhood_change_boston_january_2019.pdf

APPENDIX A

Code for cleaning split tracts

```
*Agregating tracts that split after 2018

gen GroupedTract = CensusTract


* For the tract that split from 110103 into 110104, 110105, and 110106

replace GroupedTract = 110103 if CensusTract == 110104 | CensusTract == 110105 |
CensusTract == 110106


* Repeat for other tracts that split

replace GroupedTract = 612 if CensusTract == 61201 | CensusTract == 61203 | CensusTract ==
61204

replace GroupedTract = 612 if CensusTract == 61201 | CensusTract == 61203 | CensusTract ==
61204

replace GroupedTract = 705 if CensusTract == 70501 | CensusTract == 70502

replace GroupedTract = 708 if CensusTract == 70801 | CensusTract == 70802

replace GroupedTract = 709 if CensusTract == 70901 | CensusTract == 70902

replace GroupedTract = 813 if CensusTract == 81301 | CensusTract == 81302

replace GroupedTract = 10203 if CensusTract == 10205 | CensusTract == 10206


collapse (sum) Totalpopulation Male Female White BlackorAfricanAmerican
AmericanIndianandAlaskaNativ Asian NativeHawaiianandOtherPacifi Someotherrace
HispanicorLatinooriginofan WhitealonenotHispanicorLat Native Foreignborn
NaturalizedUScitizen NotaUScitizen Bachelorsdegree Graduateorprofessionaldegree
HigherEducation Below100percentofthepoverty to149percentofthepovert
Atorabove150percentofthep Householderlivedinowneroccup Householderlivedinrenteroccu
Movedinlastyear Owneroccupiedunits Renteroccupiedunits Movedsince2018 ///

        (mean) Medianageyears Medianincomedollars Medianhomevalue Mediangrossrent
Coronaryheartdiseaseamongadu Depressionamongadults Foodinsecurityinthepast12m
Lackofsocialandemotionalsup Bingedrinkingamongadults Highbloodpressureamongadults
Shortsleepdurationamongadult Fairorpoorselfratedhealths Visitstodoctorforroutineche
Frequentmentaldistressamonga, ///

        by(GroupedTract Year)
```

APPENDIX B

Regressions and stata output

$$CHD_{2022} = \beta 0 + \beta 1 * MedAge_{08-12} + \beta 2 * pWhitenh_{08-12} + \beta 3 * pBlacknh_{08-12} + \beta 4 * pAsiannh_{08-12} + \beta 5 * pLatino_{08-12} + \beta 6 * pBachup_{08-12} + \beta 7 * MHI_{08-12} + \beta 8 * pOwnOcc_{08-12} + \beta 9 * pPov_{08-12} + \beta 10 * GentrificationStatus + \epsilon$$

regress newCHD medage0812 pwhitenh0812 pblacknh0812 pasiannh0812 platino0812 pbachup0812 mhi0812 pownocc0812 ppov0812 ib4.gentrification_status, robust

Linear regression

Number of obs	=	**50**
F(13, 36)	=	**22.12**
Prob > F	=	**0.0000**
R-squared	=	**0.8398**
Root MSE	=	**.84693**

newCHD	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
medage0812	.1558226	.0403591	3.86	0.000	.0739705	.2376747
pwhitenh0812	-.1007011	.0678156	-1.48	0.146	-.2382375	.0368354
pblacknh0812	-.0985888	.0672437	-1.47	0.151	-.2349654	.0377878
pasiannh0812	-.1407996	.0837443	-1.68	0.101	-.310641	.0290418
platino0812	-.1043769	.0686306	-1.52	0.137	-.2435662	.0348124
pbachup0812	-.0279601	.0135253	-2.07	0.046	-.0553907	-.0005295
mhi0812	-.0000522	.0000173	-3.02	0.005	-.0000874	-.0000171
pownocc0812	.0169567	.0149987	1.13	0.266	-.0134621	.0473756
ppov0812	-.006592	.0170543	-0.39	0.701	-.0411798	.0279957
gentrification_status						
1	-.325181	.4805643	-0.68	0.503	-1.299811	.6494485
2	-.8136182	.3777879	-2.15	0.038	-1.579808	-.0474287
3	-.7608281	1.858198	-0.41	0.685	-4.529429	3.007773
5	-.8546937	.3390384	-2.52	0.016	-1.542295	-.1670921
_cons	13.79162	7.386844	1.87	0.070	-1.189595	28.77283

$$Depression_{2022} = \beta 0 + \beta 1 * MedAge_{08-12} + \beta 2 * pWhitenh_{08-12} + \beta 3 * pBlacknh_{08-12} + \beta 4 * pAsiannh_{08-12} + \beta 5 * pLatino_{08-12} + \beta 6 * pBachup_{08-12} + \beta 7 * MHI_{08-12} + \beta 8 * pOwnOcc_{08-12} + \beta 9 * pPov_{08-12} + \beta 10 * GentrificationStatus + \epsilon$$

```
Linear regression                               Number of obs     =         50
                                                F(13, 36)         =      13.57
                                                Prob > F          =     0.0000
                                                R-squared         =     0.8074
                                                Root MSE          =     1.3826
```

newdepression	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
medage0812	-.2506758	.0514948	-4.87	0.000	-.3551121	-.1462394
pwhitenh0812	-.0418556	.1133309	-0.37	0.714	-.2717014	.1879901
pblacknh0812	-.1207528	.1118039	-1.08	0.287	-.3475017	.1059961
pasiannh0812	-.1301499	.1278524	-1.02	0.315	-.3894466	.1291468
platino0812	-.0827655	.1078267	-0.77	0.448	-.3014481	.1359171
pbachup0812	-.0452343	.0225401	-2.01	0.052	-.0909477	.0004791
mhi0812	-.000025	.0000359	-0.70	0.491	-.0000979	.0000479
pownocc0812	.007852	.0242585	0.32	0.748	-.0413466	.0570505
ppov0812	.0405869	.0254682	1.59	0.120	-.011065	.0922387
gentrification_status						
1	-1.56034	.809924	-1.93	0.062	-3.202942	.0822618
2	.449343	.5680477	0.79	0.434	-.7027112	1.601397
3	2.332574	1.683381	1.39	0.174	-1.08148	5.746629
5	1.128949	.6526052	1.73	0.092	-.1945956	2.452494
_cons	41.00249	12.09092	3.39	0.002	16.48097	65.52401

$$FoodInsecurity_{2022} = \beta 0 + \beta 1 * MedAge_{08-12} + \beta 2 * pWhitenh_{08-12} + \beta 3 * pBlacknh_{08-12} + \beta 4 * pAsiannh_{08-12} + \beta 5 * pLatino_{08-12} + \beta 6 * pBachup_{08-12} + \beta 7 * MHI_{08-12} + \beta 8 * pOwnOcc_{08-12} + \beta 9 * pPov_{08-12} + \beta 10 * GentrificationStatus + \epsilon$$

Linear regression

Number of obs	=	50
F(13, 36)	=	45.15
Prob > F	=	0.0000
R-squared	=	0.8711
Root MSE	=	3.3794

newfoodins	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
medage0812	-.112523	.1341671	-0.84	0.407	-.3846266	.1595805
pwhitenh0812	-.5938334	.3578491	-1.66	0.106	-1.319585	.1319182
pblacknh0812	-.4881249	.3785589	-1.29	0.205	-1.255878	.2796281
pasiannh0812	-.6522608	.4169592	-1.56	0.126	-1.497893	.1933716
platino0812	-.4467263	.3678697	-1.21	0.233	-1.192801	.2993481
pbachup0812	-.2124839	.063607	-3.34	0.002	-.3414848	-.083483
mhi0812	-.0000604	.0000701	-0.86	0.395	-.0002025	.0000817
pownocc0812	-.0365652	.0617772	-0.59	0.558	-.1618551	.0887247
ppov0812	.1664379	.0597889	2.78	0.009	.0451804	.2876955
gentrification_status						
1	-3.092451	2.362151	-1.31	0.199	-7.883114	1.698213
2	-1.98994	1.615972	-1.23	0.226	-5.267283	1.287404
3	-8.002593	3.491369	-2.29	0.028	-15.08342	-.9217689
5	.9574729	1.409272	0.68	0.501	-1.900664	3.81561
_cons	84.33623	39.72979	2.12	0.041	3.760473	164.912

$$
\begin{aligned}
&LackofSocialandEmotionalSupport_{2022} \\
&\quad = \beta 0 + \beta 1 * MedAge_{08-12} + \beta 2 * pWhitenh_{08-12} + \beta 3 * pBlacknh_{08-12} \\
&\quad + \beta 4 * pAsiannh_{08-12} + \beta 5 * pLatino_{08-12} + \beta 6 * pBachup_{08-12} + \beta 7 \\
&\quad * MHI_{08-12} + \beta 8 * pOwnOcc_{08-12} + \beta 9 * pPov_{08-12} + \beta 10 \\
&\quad * GentrificationStatus + \epsilon
\end{aligned}
$$

```
Linear regression                               Number of obs     =         50
                                                F(13, 36)         =      17.58
                                                Prob > F          =     0.0000
                                                R-squared         =     0.7634
                                                Root MSE          =     1.9871
```

newlackofsupport	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
medage0812	-.2016268	.0719617	-2.80	0.008	-.347572	-.0556816
pwhitenh0812	-.1813732	.1351013	-1.34	0.188	-.4553712	.0926249
pblacknh0812	-.1220095	.1393605	-0.88	0.387	-.4046456	.1606266
pasiannh0812	-.1390666	.1512464	-0.92	0.364	-.4458086	.1676753
platino0812	-.134219	.1368112	-0.98	0.333	-.411685	.1432471
pbachup0812	-.0937474	.0267978	-3.50	0.001	-.1480959	-.0393989
mhi0812	-.0000613	.0000438	-1.40	0.171	-.0001502	.0000276
pownocc0812	.0410555	.0336798	1.22	0.231	-.0272504	.1093613
ppov0812	.0165073	.0550172	0.30	0.766	-.0950728	.1280874
gentrification_status						
1	-.6776241	1.153669	-0.59	0.561	-3.017374	1.662125
2	-.4315034	.886407	-0.49	0.629	-2.22922	1.366213
3	-2.969893	1.569463	-1.89	0.067	-6.152912	.2131259
5	.9059855	.8504284	1.07	0.294	-.8187631	2.630734
_cons	53.63408	14.92893	3.59	0.001	23.3568	83.91136

$$
\begin{aligned}
BingDrinking_{2022} \\
&= \beta 0 + \beta 1 * MedAge_{08-12} + \beta 2 * pWhitenh_{08-12} + \beta 3 * pBlacknh_{08-12} \\
&+ \beta 4 * pAsiannh_{08-12} + \beta 5 * pLatino_{08-12} + \beta 6 * pBachup_{08-12} + \beta 7 \\
&* MHI_{08-12} + \beta 8 * pOwnOcc_{08-12} + \beta 9 * pPov_{08-12} + \beta 10 \\
&* GentrificationStatus + \epsilon
\end{aligned}
$$

Linear regression

Number of obs	=	50
F(13, 36)	=	30.53
Prob > F	=	0.0000
R-squared	=	0.8320
Root MSE	=	1.4369

newbingedrink	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
medage0812	-.1867084	.0657546	-2.84	0.007	-.3200649	-.053352
pwhitenh0812	.1959861	.1411998	1.39	0.174	-.0903805	.4823526
pblacknh0812	.1323946	.1439069	0.92	0.364	-.1594621	.4242514
pasiannh0812	.1932822	.1687935	1.15	0.260	-.1490469	.5356113
platino0812	.184102	.1422114	1.29	0.204	-.1043161	.4725201
pbachup0812	.03404	.0217416	1.57	0.126	-.010054	.0781341
mhi0812	.00008	.0000296	2.71	0.010	.0000201	.00014
pownocc0812	-.0303591	.0265645	-1.14	0.261	-.0842344	.0235162
ppov0812	-.0383598	.0260273	-1.47	0.149	-.0911457	.0144261
gentrification_status						
1	.6157333	1.039878	0.59	0.557	-1.493238	2.724704
2	.9050499	.665041	1.36	0.182	-.4437159	2.253816
3	1.871741	3.002067	0.62	0.537	-4.216732	7.960214
5	.9060285	.5764231	1.57	0.125	-.2630117	2.075069
_cons	4.6489	15.06224	0.31	0.759	-25.89875	35.19655

$$ShortSleepDuration_{2022} = \beta 0 + \beta 1 * MedAge_{08-12} + \beta 2 * pWhitenh_{08-12} + \beta 3 * pBlacknh_{08-12} + \beta 4 * pAsiannh_{08-12} + \beta 5 * pLatino_{08-12} + \beta 6 * pBachup_{08-12} + \beta 7 * MHI_{08-12} + \beta 8 * pOwnOcc_{08-12} + \beta 9 * pPov_{08-12} + \beta 10 * GentrificationStatus + \epsilon$$

Linear regression

Number of obs	=	**50**
F(13, 36)	=	**37.96**
Prob > F	=	**0.0000**
R-squared	=	**0.9010**
Root MSE	=	**1.3047**

newshortsleep	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
medage0812	-.118377	.0432071	-2.74	0.010	-.206005	-.030749
pwhitenh0812	-.1853427	.1092718	-1.70	0.098	-.4069562	.0362708
pblacknh0812	-.0852421	.1111102	-0.77	0.448	-.310584	.1400997
pasiannh0812	-.1519045	.1267682	-1.20	0.239	-.4090024	.1051934
platino0812	-.1379485	.1075249	-1.28	0.208	-.3560192	.0801221
pbachup0812	-.0828148	.0222616	-3.72	0.001	-.1279634	-.0376662
mhi0812	-.0000318	.0000288	-1.10	0.277	-.0000902	.0000266
pownocc0812	.0345557	.0227403	1.52	0.137	-.0115637	.080675
ppov0812	.0382101	.0198128	1.93	0.062	-.0019722	.0783924
gentrification_status						
1	-1.072976	.8195231	-1.31	0.199	-2.735046	.5890941
2	-.1943498	.5707633	-0.34	0.735	-1.351911	.9632119
3	-2.013554	.9799007	-2.05	0.047	-4.000884	-.0262228
5	.8116479	.6103476	1.33	0.192	-.4261943	2.04949
_cons	55.3579	11.52273	4.80	0.000	31.98872	78.72708

$$FairorPoorSRH_{2022} = \beta0 + \beta1 * MedAge_{08-12} + \beta2 * pWhitenh_{08-12} + \beta3 * pBlacknh_{08-12} + \beta4 * pAsiannh_{08-12} + \beta5 * pLatino_{08-12} + \beta6 * pBachup_{08-12} + \beta7 * MHI_{08-12} + \beta8 * pOwnOcc_{08-12} + \beta9 * pPov_{08-12} + \beta10 * GentrificationStatus + \epsilon$$

Linear regression

Number of obs	=	50
F(13, 36)	=	37.87
Prob > F	=	0.0000
R-squared	=	0.8724
Root MSE	=	2.3327

newfairorpoorsrh	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
medage0812	.0292635	.1046441	0.28	0.781	-.1829646	.2414916
pwhitenh0812	-.4578093	.2355588	-1.94	0.060	-.9355447	.019926
pblacknh0812	-.409282	.2443628	-1.67	0.103	-.9048726	.0863087
pasiannh0812	-.5049881	.2778939	-1.82	0.078	-1.068583	.0586069
platino0812	-.3477618	.2404679	-1.45	0.157	-.8354533	.1399298
pbachup0812	-.1546758	.0417623	-3.70	0.001	-.2393736	-.0699779
mhi0812	-.0000896	.0000508	-1.76	0.086	-.0001926	.0000134
pownocc0812	.020963	.0425123	0.49	0.625	-.0652559	.107182
ppov0812	.0557073	.0390275	1.43	0.162	-.0234442	.1348589
gentrification_status						
1	-1.899332	1.609492	-1.18	0.246	-5.163533	1.364869
2	-1.438873	1.140767	-1.26	0.215	-3.752456	.8747098
3	-1.572604	3.87631	-0.41	0.687	-9.434125	6.288916
5	.189823	.9059311	0.21	0.835	-1.64749	2.027136
_cons	65.95692	25.82183	2.55	0.015	13.58782	118.326

$$RoutineDocCheckups_{2022} = \beta 0 + \beta 1 * MedAge_{08-12} + \beta 2 * pWhitenh_{08-12} + \beta 3 * pBlacknh_{08-12} + \beta 4 * pAsiannh_{08-12} + \beta 5 * pLatino_{08-12} + \beta 6 * pBachup_{08-12} + \beta 7 * MHI_{08-12} + \beta 8 * pOwnOcc_{08-12} + \beta 9 * pPov_{08-12} + \beta 10 * GentrificationStatus + \epsilon$$

Linear regression

Number of obs	=	50
F(13, 36)	=	24.63
Prob > F	=	0.0000
R-squared	=	0.9053
Root MSE	=	1.2076

newdocvisits	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
medage0812	.2924309	.053805	5.44	0.000	.1833094	.4015525
pwhitenh0812	-.006625	.1068065	-0.06	0.951	-.2232387	.2099887
pblacknh0812	.0788496	.1091667	0.72	0.475	-.1425508	.30025
pasiannh0812	-.0531759	.1240593	-0.43	0.671	-.3047799	.198428
platino0812	-.0434168	.1060711	-0.41	0.685	-.258539	.1717053
pbachup0812	.0050129	.0145048	0.35	0.732	-.0244042	.03443
mhi0812	-.0000397	.0000273	-1.45	0.155	-.0000951	.0000157
pownocc0812	.038473	.0194692	1.98	0.056	-.0010122	.0779583
ppov0812	.0307428	.0359388	0.86	0.398	-.0421446	.1036302
gentrification_status						
1	.08338	.7061454	0.12	0.907	-1.348749	1.515509
2	-.6240961	.5138854	-1.21	0.232	-1.666304	.4181117
3	-1.735789	2.073462	-0.84	0.408	-5.940964	2.469386
5	-1.076923	.468942	-2.30	0.028	-2.027981	-.1258646
_cons	66.38659	12.134	5.47	0.000	41.7777	90.99547

$$FrequentMentalDistress_{2022} = \beta0 + \beta1 * MedAge_{08-12} + \beta2 * pWhitenh_{08-12} + \beta3 * pBlacknh_{08-12} + \beta4 * pAsiannh_{08-12} + \beta5 * pLatino_{08-12} + \beta6 * pBachup_{08-12} + \beta7 * MHI_{08-12} + \beta8 * pOwnOcc_{08-12} + \beta9 * pPov_{08-12} + \beta10 * GentrificationStatus + \epsilon$$

Linear regression

Number of obs	=	**50**
F(13, 36)	=	**13.81**
Prob > F	=	**0.0000**
R-squared	=	**0.7818**
Root MSE	=	**1.9645**

newmentaldistress	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
medage0812	**-.3976402**	**.0733034**	**-5.42**	**0.000**	**-.5463065**	**-.248974**
pwhitenh0812	**-.1048303**	**.1832729**	**-0.57**	**0.571**	**-.4765249**	**.2668643**
pblacknh0812	**-.1476377**	**.180577**	**-0.82**	**0.419**	**-.5138648**	**.2185894**
pasiannh0812	**-.1620401**	**.2046515**	**-0.79**	**0.434**	**-.5770925**	**.2530124**
platino0812	**-.1371396**	**.1719138**	**-0.80**	**0.430**	**-.485797**	**.2115179**
pbachup0812	**-.0970827**	**.0329993**	**-2.94**	**0.006**	**-.1640084**	**-.0301569**
mhi0812	**-.0000621**	**.0000537**	**-1.16**	**0.255**	**-.000171**	**.0000468**
pownocc0812	**.0303075**	**.0347979**	**0.87**	**0.390**	**-.040266**	**.100881**
ppov0812	**.0534379**	**.0423024**	**1.26**	**0.215**	**-.0323553**	**.1392312**
gentrification_status						
1	**-2.200403**	**.9829722**	**-2.24**	**0.031**	**-4.193963**	**-.2068432**
2	**.1905534**	**.6383053**	**0.30**	**0.767**	**-1.10399**	**1.485097**
3	**1.118412**	**1.968586**	**0.57**	**0.573**	**-2.874066**	**5.11089**
5	**1.726663**	**.9258015**	**1.87**	**0.070**	**-.1509493**	**3.604275**
_cons	**48.05762**	**19.24984**	**2.50**	**0.017**	**9.017121**	**87.09811**

$$SociallyIsolated_{2022} = \beta 0 + \beta 1 * MedAge_{08-12} + \beta 2 * pWhitenh_{08-12} + \beta 3 * pBlacknh_{08-12} + \beta 4 * pAsiannh_{08-12} + \beta 5 * pLatino_{08-12} + \beta 6 * pBachup_{08-12} + \beta 7 * MHI_{08-12} + \beta 8 * pOwnOcc_{08-12} + \beta 9 * pPov_{08-12} + \beta 10 * GentrificationStatus + \epsilon$$

Linear regression

Number of obs	=	50
F(13, 36)	=	14.32
Prob > F	=	0.0000
R-squared	=	0.7569
Root MSE	=	1.8659

newsociallyisolated	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
medage0812	-.3686801	.0751463	-4.91	0.000	-.521084	-.2162763
pwhitenh0812	-.0163136	.1518218	-0.11	0.915	-.3242225	.2915953
pblacknh0812	-.0347528	.1541196	-0.23	0.823	-.3473218	.2778162
pasiannh0812	-.0349804	.1742014	-0.20	0.842	-.3882772	.3183164
platino0812	-.0321161	.1493483	-0.22	0.831	-.3350085	.2707763
pbachup0812	-.0664317	.0276626	-2.40	0.022	-.122534	-.0103294
mhi0812	-.0000343	.000046	-0.75	0.461	-.0001277	.0000591
pownocc0812	.0104335	.032447	0.32	0.750	-.0553721	.0762392
ppov0812	.0277379	.0556179	0.50	0.621	-.0850605	.1405363
gentrification_status						
1	-1.176442	1.046586	-1.12	0.268	-3.299017	.9461332
2	.2895016	.6876738	0.42	0.676	-1.105165	1.684169
3	-.9106934	2.452561	-0.37	0.713	-5.884718	4.063331
5	1.493714	.779501	1.92	0.063	-.0871868	3.074616
_cons	54.91408	16.57829	3.31	0.002	21.29175	88.53642

$$CHD_{2022} = \beta 0 + \beta 1 * MedAge_{08-12} + \beta 2 * pWhitenh_{08-12} + \beta 3 * pBlacknh_{08-12} + \beta 4 * pAsiannh_{08-12} + \beta 5 * pLatino_{08-12} + \beta 6 * pBachup_{08-12} + \beta 7 * MHI_{08-12} + \beta 8 * pOwnOcc_{08-12} + \beta 9 * pPov_{08-12} + \beta 10 * GentrificationStatus * pBlack_{2022} + \epsilon$$

```
Linear regression                               Number of obs     =         50
                                                F(16, 31)         =          .
                                                Prob > F          =          .
                                                R-squared         =     0.9179
                                                Root MSE          =     .65361
```

newCHD	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
medage0812	.2224586	.043964	5.06	0.000	.1327934	.3121237
pwhitenh0812	-.0222686	.0476449	-0.47	0.643	-.1194411	.0749039
pblacknh0812	-.018072	.0475595	-0.38	0.707	-.1150703	.0789263
pasiannh0812	-.0114176	.0566802	-0.20	0.842	-.1270177	.1041825
platino0812	-.0213599	.0478061	-0.45	0.658	-.1188611	.0761412
pbachup0812	-.0367933	.0108823	-3.38	0.002	-.058988	-.0145987
mhi0812	-.0000497	.0000172	-2.90	0.007	-.0000847	-.0000147
pownocc0812	-.0023418	.0112557	-0.21	0.837	-.0252979	.0206144
ppov0812	-.0211493	.015876	-1.33	0.193	-.0535287	.0112301
gentrification_status						
1	-.893587	.4306246	-2.08	0.046	-1.771852	-.0153224
2	-.9598873	.418734	-2.29	0.029	-1.813901	-.1058738
3	9.19132	1.217383	7.55	0.000	6.708451	11.67419
5	-.3745081	.4933191	-0.76	0.453	-1.380639	.6316229
pBlack22	.000282	.0223664	0.01	0.990	-.0453346	.0458986
gentrification_status#c.pBlack22						
1	.0299063	.0218217	1.37	0.180	-.0145994	.074412
2	-.0076673	.0123487	-0.62	0.539	-.0328526	.0175181
3	-1.459895	.2049958	-7.12	0.000	-1.877986	-1.041803
5	-.0073998	.013104	-0.56	0.576	-.0341255	.0193259
_cons	4.524135	5.728533	0.79	0.436	-7.159285	16.20756

$$Depression_{2022} = \beta 0 + \beta 1 * MedAge_{08-12} + \beta 2 * pWhitenh_{08-12} + \beta 3 * pBlacknh_{08-12} + \beta 4 * pAsiannh_{08-12} + \beta 5 * pLatino_{08-12} + \beta 6 * pBachup_{08-12} + \beta 7 * MHI_{08-12} + \beta 8 * pOwnOcc_{08-12} + \beta 9 * pPov_{08-12} + \beta 10 * GentrificationStatus * pBlack_{2022} + \epsilon$$

Linear regression

Number of obs	=	50
F(16, 31)	=	.
Prob > F	=	.
R-squared	=	0.8358
Root MSE	=	1.3759

newdepression	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
medage0812	-.3078912	.0614178	-5.01	0.000	-.4331536	-.1826289
pwhitenh0812	-.1085283	.1270683	-0.85	0.400	-.3676858	.1506292
pblacknh0812	-.15126	.1399377	-1.08	0.288	-.4366648	.1341448
pasiannh0812	-.2268126	.1487335	-1.52	0.137	-.5301566	.0765314
platino0812	-.1468863	.121649	-1.21	0.236	-.394991	.1012184
pbachup0812	-.0355571	.0253893	-1.40	0.171	-.0873389	.0162247
mhi0812	-.000028	.0000401	-0.70	0.490	-.0001098	.0000538
pownocc0812	.0206491	.027568	0.75	0.459	-.0355761	.0768743
ppov0812	.0313028	.0301311	1.04	0.307	-.03015	.0927555
gentrification_status						
1	-2.2094	1.373933	-1.61	0.118	-5.011555	.5927542
2	.5577636	.8016857	0.70	0.492	-1.077285	2.192812
3	-6.241366	1.928097	-3.24	0.003	-10.17375	-2.308987
5	.9393817	1.021434	0.92	0.365	-1.143847	3.02261
pBlack22	-.0412515	.0500676	-0.82	0.416	-.143365	.060862
gentrification_status#c.pBlack22						
1	.0688591	.0729562	0.94	0.353	-.079936	.2176542
2	.0014369	.025317	0.06	0.955	-.0501975	.0530712
3	1.219302	.3386222	3.60	0.001	.5286779	1.909927
5	.009151	.0243629	0.38	0.710	-.0405376	.0588395
_cons	49.22348	13.6245	3.61	0.001	21.43613	77.01084

$$Food\ insecurity_{2022} = \beta 0 + \beta 1 * MedAge_{08-12} + \beta 2 * pWhitenh_{08-12} + \beta 3 * pBlacknh_{08-12} + \beta 4 * pAsiannh_{08-12} + \beta 5 * pLatino_{08-12} + \beta 6 * pBachup_{08-12} + \beta 7 * MHI_{08-12} + \beta 8 * pOwnOcc_{08-12} + \beta 9 * pPov_{08-12} + \beta 10 * GentrificationStatus * pBlack_{2022} + \epsilon$$

```
Linear regression                               Number of obs     =         50
                                                F(16, 31)         =          .
                                                Prob > F          =          .
                                                R-squared         =     0.8887
                                                Root MSE          =     3.3846
```

newfoodins	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
medage0812	.0560265	.1726044	0.32	0.748	-.2960024	.4080554
pwhitenh0812	-.5401119	.3730249	-1.45	0.158	-1.300901	.2206774
pblacknh0812	-.383241	.3710045	-1.03	0.310	-1.13991	.3734276
pasiannh0812	-.5054853	.4402559	-1.15	0.260	-1.403393	.3924225
platino0812	-.3753278	.3771683	-1.00	0.327	-1.144568	.393912
pbachup0812	-.223293	.0677296	-3.30	0.002	-.3614283	-.0851576
mhi0812	-.000067	.0000656	-1.02	0.315	-.0002007	.0000667
pownocc0812	-.0953622	.071882	-1.33	0.194	-.2419665	.0512422
ppov0812	.1087708	.0732989	1.48	0.148	-.0407233	.2582649
gentrification_status						
1	-3.634075	3.161052	-1.15	0.259	-10.08108	2.812933
2	-1.102086	1.851536	-0.60	0.556	-4.878319	2.674147
3	9.192553	5.921152	1.55	0.131	-2.883716	21.26882
5	3.809755	2.724795	1.40	0.172	-1.7475	9.367011
pBlack22	-.0184857	.0997062	-0.19	0.854	-.2218379	.1848664
gentrification_status#c.pBlack22						
1	.0559445	.150276	0.37	0.712	-.2505453	.3624344
2	-.081333	.0550311	-1.48	0.150	-.1935697	.0309038
3	-2.558899	1.024196	-2.50	0.018	-4.647761	-.4700364
5	-.0908723	.0815963	-1.11	0.274	-.257289	.0755444
_cons	75.36642	41.14125	1.83	0.077	-8.541706	159.2745

$$Lack\ of\ social\ or\ emotional\ support_{2022} = \beta 0 + \beta 1 * MedAge_{08-12} + \beta 2 * pWhitenh_{08-12} + \beta 3 * pBlacknh_{08-12} + \beta 4 * pAsiannh_{08-12} + \beta 5 * pLatino_{08-12} + \beta 6 * pBachup_{08-12} + \beta 7 * MHI_{08-12} + \beta 8 * pOwnOcc_{08-12} + \beta 9 * pPov_{08-12} + \beta 10 * GentrificationStatus * pBlack_{2022} + \epsilon$$

Linear regression

Number of obs	=	50
F(16, 31)	=	.
Prob > F	=	.
R-squared	=	0.7975
Root MSE	=	1.981

newlackofsupport	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
medage0812	-.1361383	.0939943	-1.45	0.158	-.327841	.0555644
pwhitenh0812	-.2139656	.1144034	-1.87	0.071	-.447293	.0193618
pblacknh0812	-.1733975	.1310687	-1.32	0.196	-.4407137	.0939188
pasiannh0812	-.1643844	.1396218	-1.18	0.248	-.449145	.1203761
platino0812	-.1690694	.1154934	-1.46	0.153	-.4046197	.0664809
pbachup0812	-.0972601	.0301523	-3.23	0.003	-.1587561	-.0357642
mhi0812	-.0000648	.0000451	-1.44	0.161	-.0001569	.0000272
pownocc0812	.0186742	.0358879	0.52	0.607	-.0545197	.0918681
ppov0812	.0206696	.0580744	0.36	0.724	-.0977739	.1391132
gentrification_status						
1	1.293561	1.35596	0.95	0.347	-1.471938	4.05906
2	.6800322	1.098031	0.62	0.540	-1.559417	2.919481
3	1.530626	3.596267	0.43	0.673	-5.804009	8.865261
5	2.218541	1.367706	1.62	0.115	-.5709136	5.007995
pBlack22	.0474991	.0713297	0.67	0.510	-.0979788	.1929771
gentrification_status#c.pBlack22						
1	-.1346087	.081551	-1.65	0.109	-.3009331	.0317158
2	-.0631637	.0329214	-1.92	0.064	-.1303075	.00398
3	-.6303756	.6363934	-0.99	0.330	-1.928308	.6675573
5	-.0616986	.05087	-1.21	0.234	-.1654486	.0420514
_cons	54.83762	13.30096	4.12	0.000	27.71014	81.9651

$$\begin{aligned} Binge\ drinking_{2022} &= \beta 0 + \beta 1 * MedAge_{08-12} + \beta 2 * pWhitenh_{08-12} + \beta 3 * pBlacknh_{08-12} \\ &+ \beta 4 * pAsiannh_{08-12} + \beta 5 * pLatino_{08-12} + \beta 6 * pBachup_{08-12} + \beta 7 \\ &* MHI_{08-12} + \beta 8 * pOwnOcc_{08-12} + \beta 9 * pPov_{08-12} + \beta 10 \\ &* GentrificationStatus * pBlack_{2022} + \epsilon \end{aligned}$$

Linear regression

Number of obs	=	50
F(16, 31)	=	.
Prob > F	=	.
R-squared	=	0.9128
Root MSE	=	1.1156

newbingedrink	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
medage0812	-.304577	.0559876	-5.44	0.000	-.4187644	-.1903896
pwhitenh0812	.0443444	.1053109	0.42	0.677	-.1704387	.2591275
pblacknh0812	.0239832	.1074939	0.22	0.825	-.1952521	.2432186
pasiannh0812	-.0359517	.1188206	-0.30	0.764	-.2782879	.2063844
platino0812	.0240064	.0998106	0.24	0.812	-.1795586	.2275714
pbachup0812	.046111	.0203718	2.26	0.031	.0045623	.0876596
mhi0812	.0000787	.0000299	2.63	0.013	.0000177	.0001398
pownocc0812	-.0038807	.0240926	-0.16	0.873	-.0530178	.0452564
ppov0812	-.0255631	.0256082	-1.00	0.326	-.0777914	.0266652
gentrification_status						
1	1.590103	1.031161	1.54	0.133	-.5129638	3.693169
2	1.46884	.7085136	2.07	0.047	.0238174	2.913863
3	-15.03038	1.720889	-8.73	0.000	-18.54016	-11.52061
5	.4487192	.9134301	0.49	0.627	-1.414234	2.311672
pBlack22	-.048266	.0314695	-1.53	0.135	-.1124486	.0159165
gentrification_status#c.pBlack22						
1	-.0405877	.0494422	-0.82	0.418	-.1414257	.0602502
2	-.0052026	.0174352	-0.30	0.767	-.0407619	.0303568
3	2.430091	.2658649	9.14	0.000	1.887856	2.972326
5	.0079379	.0248148	0.32	0.751	-.0426722	.058548
_cons	22.6297	10.74646	2.11	0.043	.7121494	44.54726

$$Short\ sleep_{2022} = \beta0 + \beta1 * MedAge_{08-12} + \beta2 * pWhitenh_{08-12} + \beta3 * pBlacknh_{08-12} + \beta4 * pAsiannh_{08-12} + \beta5 * pLatino_{08-12} + \beta6 * pBachup_{08-12} + \beta7 * MHI_{08-12} + \beta8 * pOwnOcc_{08-12} + \beta9 * pPov_{08-12} + \beta10 * GentrificationStatus * pBlack_{2022} + \epsilon$$

Linear regression			
	Number of obs	=	50
	F(16, 31)	=	.
	Prob > F	=	.
	R-squared	=	0.9065
	Root MSE	=	1.3661

newshortsleep	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
medage0812	-.0773655	.0618101	-1.25	0.220	-.2034279	.0486969
pwhitenh0812	-.1647084	.1156912	-1.42	0.165	-.4006621	.0712454
pblacknh0812	-.0927375	.1300829	-0.71	0.481	-.3580433	.1725683
pasiannh0812	-.1161942	.1379386	-0.84	0.406	-.3975219	.1651335
platino0812	-.117813	.1134295	-1.04	0.307	-.3491539	.1135279
pbachup0812	-.0852448	.0247581	-3.44	0.002	-.1357392	-.0347505
mhi0812	-.0000317	.0000306	-1.04	0.307	-.0000941	.0000306
pownocc0812	.0243164	.0276593	0.88	0.386	-.032095	.0807279
ppov0812	.0430778	.0262116	1.64	0.110	-.0103811	.0965367
gentrification_status						
1	-.476319	1.158309	-0.41	0.684	-2.838706	1.886068
2	.1671323	.8242587	0.20	0.841	-1.513954	1.848219
3	2.633497	2.120871	1.24	0.224	-1.692048	6.959042
5	1.127066	1.058867	1.06	0.295	-1.032507	3.286639
pBlack22	.0395608	.0495564	0.80	0.431	-.06151	.1406317
gentrification_status#c.pBlack22						
1	-.0468725	.0464835	-1.01	0.321	-.1416763	.0479313
2	-.0251017	.0266369	-0.94	0.353	-.0794281	.0292246
3	-.6473968	.3595827	-1.80	0.082	-1.380771	.085977
5	-.0160074	.02702	-0.59	0.558	-.071115	.0391001
_cons	51.93733	12.24458	4.24	0.000	26.96435	76.91031

$$Fair\ or\ poor\ srh_{2022} = \beta 0 + \beta 1 * MedAge_{08-12} + \beta 2 * pWhitenh_{08-12} + \beta 3 * pBlacknh_{08-12} + \beta 4 * pAsiannh_{08-12} + \beta 5 * pLatino_{08-12} + \beta 6 * pBachup_{08-12} + \beta 7 * MHI_{08-12} + \beta 8 * pOwnOcc_{08-12} + \beta 9 * pPov_{08-12} + \beta 10 * GentrificationStatus * pBlack_{2022} + \epsilon$$

```
Linear regression                               Number of obs     =         50
                                                F(16, 31)         =          .
                                                Prob > F          =          .
                                                R-squared         =     0.9130
                                                Root MSE          =     2.0762
```

newfairorpoorsrh	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
medage0812	.1811373	.1256766	1.44	0.160	-.0751819	.4374565
pwhitenh0812	-.3279993	.2143638	-1.53	0.136	-.7651971	.1091985
pblacknh0812	-.2296134	.2154416	-1.07	0.295	-.6690094	.2097827
pasiannh0812	-.2606051	.2551808	-1.02	0.315	-.7810499	.2598397
platino0812	-.2014283	.214063	-0.94	0.354	-.6380127	.2351562
pbachup0812	-.1701293	.0391887	-4.34	0.000	-.2500551	-.0902035
mhi0812	-.0000882	.0000509	-1.73	0.093	-.0001919	.0000155
pownocc0812	-.0296674	.0424687	-0.70	0.490	-.1162829	.0569482
ppov0812	.0002179	.0553713	0.00	0.997	-.1127126	.1131485
gentrification_status						
1	-3.623082	1.700964	-2.13	0.041	-7.092222	-.1539425
2	-1.330824	1.152045	-1.16	0.257	-3.680434	1.018786
3	18.54508	4.47014	4.15	0.000	9.428167	27.66199
5	2.015658	1.722485	1.17	0.251	-1.497373	5.528689
pBlack22	-.037708	.0725516	-0.52	0.607	-.185678	.1102619
gentrification_status#c.pBlack22						
1	.1230575	.075665	1.63	0.114	-.0312624	.2773774
2	-.0434622	.0406799	-1.07	0.294	-.1264294	.039505
3	-2.993713	.7450311	-4.02	0.000	-4.513214	-1.474212
5	-.0395807	.0442015	-0.90	0.377	-.1297301	.0505688
_cons	49.97943	23.89242	2.09	0.045	1.250523	98.70833

$$
\begin{aligned}
Routine\ doctor\ visits_{2022} &= \beta 0 + \beta 1 * MedAge_{08-12} + \beta 2 * pWhitenh_{08-12} + \beta 3 * pBlacknh_{08-12} \\
&+ \beta 4 * pAsiannh_{08-12} + \beta 5 * pLatino_{08-12} + \beta 6 * pBachup_{08-12} + \beta 7 \\
&* MHI_{08-12} + \beta 8 * pOwnOcc_{08-12} + \beta 9 * pPov_{08-12} + \beta 10 \\
&* GentrificationStatus * pBlack_{2022} + \epsilon
\end{aligned}
$$

Linear regression

Number of obs	=	50
F(16, 31)	=	.
Prob > F	=	.
R-squared	=	0.9384
Root MSE	=	1.0496

newdocvisits	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
medage0812	.3675311	.0541404	6.79	0.000	.2571111	.4779511
pwhitenh0812	.1071674	.0871157	1.23	0.228	-.0705061	.284841
pblacknh0812	.1404589	.1000194	1.40	0.170	-.063532	.3444498
pasiannh0812	.1059606	.1044245	1.01	0.318	-.1070145	.3189357
platino0812	.0766078	.0859346	0.89	0.380	-.098657	.2518726
pbachup0812	-.0013453	.0165515	-0.08	0.936	-.0351023	.0324117
mhi0812	-.0000405	.0000281	-1.44	0.161	-.0000979	.0000169
pownocc0812	.0264309	.0216282	1.22	0.231	-.0176801	.0705418
ppov0812	.0283266	.0290592	0.97	0.337	-.0309401	.0875933
gentrification_status						
1	-.7395359	.9983761	-0.74	0.464	-2.775737	1.296666
2	-1.320635	.5823741	-2.27	0.030	-2.508395	-.1328756
3	9.034156	1.997811	4.52	0.000	4.959594	13.10872
5	-1.069496	.6693218	-1.60	0.120	-2.434587	.2955947
pBlack22	.0530995	.0425609	1.25	0.222	-.0337041	.1399031
gentrification_status#c.pBlack22						
1	.0320913	.0591173	0.54	0.591	-.0884792	.1526617
2	.022157	.0204851	1.08	0.288	-.0196226	.0639366
3	-1.523648	.3534053	-4.31	0.000	-2.244423	-.8028733
5	.0018674	.0204734	0.09	0.928	-.0398885	.0436232
_cons	53.13831	10.08309	5.27	0.000	32.57372	73.7029

$$
\begin{aligned}
Mental\ distress_{2022} &= \beta 0 + \beta 1 * MedAge_{08-12} + \beta 2 * pWhitenh_{08-12} + \beta 3 * pBlacknh_{08-12} \\
&+ \beta 4 * pAsiannh_{08-12} + \beta 5 * pLatino_{08-12} + \beta 6 * pBachup_{08-12} + \beta 7 \\
&* MHI_{08-12} + \beta 8 * pOwnOcc_{08-12} + \beta 9 * pPov_{08-12} + \beta 10 \\
&* GentrificationStatus * pBlack_{2022} + \epsilon
\end{aligned}
$$

Linear regression

Number of obs	=	50
F(16, 31)	=	.
Prob > F	=	.
R-squared	=	0.7991
Root MSE	=	2.0309

newmentaldistress	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
medage0812	-.4422802	.0976878	-4.53	0.000	-.6415159	-.2430446
pwhitenh0812	-.1853219	.2030129	-0.91	0.368	-.5993695	.2287256
pblacknh0812	-.1915403	.2314633	-0.83	0.414	-.6636129	.2805323
pasiannh0812	-.2703635	.2387442	-1.13	0.266	-.7572856	.2165586
platino0812	-.2142622	.1919073	-1.12	0.273	-.6056596	.1771353
pbachup0812	-.0862346	.0380141	-2.27	0.030	-.1637649	-.0087043
mhi0812	-.0000663	.0000592	-1.12	0.271	-.000187	.0000543
pownocc0812	.0378837	.0414665	0.91	0.368	-.0466878	.1224552
ppov0812	.0414942	.0484338	0.86	0.398	-.0572872	.1402755
gentrification_status						
1	-2.5993	1.776445	-1.46	0.153	-6.222383	1.023782
2	.6839135	.9747735	0.70	0.488	-1.30415	2.671977
3	-6.958793	2.730334	-2.55	0.016	-12.52735	-1.39024
5	1.853485	1.551975	1.19	0.241	-1.311788	5.018759
pBlack22	-.0339412	.0703292	-0.48	0.633	-.1773784	.1094961
gentrification_status#c.pBlack22						
1	.0583087	.1001375	0.58	0.565	-.1459232	.2625405
2	-.0212947	.0358644	-0.59	0.557	-.0944405	.0518512
3	1.149785	.5269625	2.18	0.037	.0750375	2.224532
5	-.0040803	.038405	-0.11	0.916	-.0824077	.0742472
_cons	57.2035	21.25353	2.69	0.011	13.85664	100.5504

$$SociallyIsolated_{2022} = \beta 0 + \beta 1 * MedAge_{08-12} + \beta 2 * pWhitenh_{08-12} + \beta 3 * pBlacknh_{08-12} + \beta 4 * pAsiannh_{08-12} + \beta 5 * pLatino_{08-12} + \beta 6 * pBachup_{08-12} + \beta 7 * MHI_{08-12} + \beta 8 * pOwnOcc_{08-12} + \beta 9 * pPov_{08-12} + \beta 10 * GentrificationStatus * pBlack_{2022} + \epsilon$$

```
Linear regression                               Number of obs     =         50
                                                F(16, 31)         =          .
                                                Prob > F          =          .
                                                R-squared         =     0.7972
                                                Root MSE          =     1.8363
```

newsociallyisolated	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
medage0812	-.4086893	.0969147	-4.22	0.000	-.6063481	-.2110305
pwhitenh0812	-.1385342	.1326264	-1.04	0.304	-.4090276	.1319592
pblacknh0812	-.1371345	.1541825	-0.89	0.381	-.4515919	.1773228
pasiannh0812	-.2051246	.1588163	-1.29	0.206	-.5290325	.1187833
platino0812	-.1569065	.1284332	-1.22	0.231	-.4188476	.1050347
pbachup0812	-.0568344	.0287616	-1.98	0.057	-.1154942	.0018253
mhi0812	-.0000403	.0000481	-0.84	0.409	-.0001383	.0000578
pownocc0812	.0159138	.0352065	0.45	0.654	-.0558904	.087718
ppov0812	.0309779	.0540527	0.57	0.571	-.0792634	.1412191
gentrification_status						
1	.0320484	1.360386	0.02	0.981	-2.742476	2.806573
2	1.217418	.9244587	1.32	0.198	-.6680276	3.102864
3	-10.39802	3.220024	-3.23	0.003	-16.9653	-3.830738
5	2.003293	1.304745	1.54	0.135	-.6577522	4.664339
pBlack22	-.0062091	.0598737	-0.10	0.918	-.1283222	.115904
gentrification_status#c.pBlack22						
1	-.058096	.0909611	-0.64	0.528	-.2436125	.1274204
2	-.0370944	.0327008	-1.13	0.265	-.103788	.0295992
3	1.375646	.6057771	2.27	0.030	.140155	2.611136
5	-.0314833	.0429432	-0.73	0.469	-.1190665	.0561
_cons	67.86433	14.95678	4.54	0.000	37.35978	98.36889

$$CHD_{2022} = \beta 0 + \beta 1 * MedAge_{08-12} + \beta 2 * pWhitenh_{08-12} + \beta 3 * pBlacknh_{08-12} + \beta 4 * pAsiannh_{08-12} + \beta 5 * pLatino_{08-12} + \beta 6 * pBachup_{08-12} + \beta 7 * MHI_{08-12} + \beta 8 * pOwnOcc_{08-12} + \beta 9 * pPov_{08-12} + \beta 10 * GentrificationStatus * pMinority_{2022} + \epsilon$$

Linear regression

Number of obs	=	50
F(16, 31)	=	.
Prob > F	=	.
R-squared	=	0.9265
Root MSE	=	.61818

newCHD	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
medage0812	.1890367	.0337065	5.61	0.000	.1202919	.2577815
pwhitenh0812	-.0338634	.0448287	-0.76	0.456	-.1252922	.0575654
pblacknh0812	-.0138314	.04421	-0.31	0.756	-.1039983	.0763355
pasiannh0812	-.0077469	.0527082	-0.15	0.884	-.1152459	.0997521
platino0812	-.0161063	.0445367	-0.36	0.720	-.1069394	.0747268
pbachup0812	-.046414	.0139988	-3.32	0.002	-.0749647	-.0178634
mhi0812	-.0000496	.0000155	-3.20	0.003	-.0000811	-.000018
pownocc0812	.0018343	.0116074	0.16	0.875	-.021839	.0255077
ppov0812	-.0205755	.0125019	-1.65	0.110	-.0460732	.0049223
gentrification_status						
1	1.978048	1.929765	1.03	0.313	-1.957735	5.913831
2	-.6122844	1.400566	-0.44	0.665	-3.468758	2.244189
3	19.51278	2.778905	7.02	0.000	13.84517	25.1804
5	-.670892	1.086573	-0.62	0.541	-2.886973	1.545189
pMinority22	-.027849	.0160964	-1.73	0.094	-.0606778	.0049799
gentrification_status#c.pMinority22						
1	-.0328832	.023702	-1.39	0.175	-.0812237	.0154574
2	-.007617	.0216553	-0.35	0.727	-.0517832	.0365492
3	-.4470057	.0628975	-7.11	0.000	-.575286	-.3187254
5	.0047076	.0154868	0.30	0.763	-.0268779	.0362931
_cons	7.718289	5.539658	1.39	0.173	-3.579918	19.0165

$$Depression_{2022} = \beta 0 + \beta 1 * MedAge_{08-12} + \beta 2 * pWhitenh_{08-12} + \beta 3 * pBlacknh_{08-12} + \beta 4 * pAsiannh_{08-12} + \beta 5 * pLatino_{08-12} + \beta 6 * pBachup_{08-12} + \beta 7 * MHI_{08-12} + \beta 8 * pOwnOcc_{08-12} + \beta 9 * pPov_{08-12} + \beta 10 * GentrificationStatus * pMinority_{2022} + \epsilon$$

```
Linear regression                               Number of obs     =         50
                                                F(16, 31)         =          .
                                                Prob > F          =          .
                                                R-squared         =     0.8465
                                                Root MSE          =     1.3303
```

newdepression	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
medage0812	-.3068506	.0676482	-4.54	0.000	-.4448201	-.1688811
pwhitenh0812	-.1108847	.1396734	-0.79	0.433	-.3957504	.1739811
pblacknh0812	-.1859263	.1289728	-1.44	0.159	-.4489681	.0771154
pasiannh0812	-.2490233	.151804	-1.64	0.111	-.5586297	.0605831
platino0812	-.1658447	.1292867	-1.28	0.209	-.4295267	.0978373
pbachup0812	-.0431592	.0344585	-1.25	0.220	-.1134376	.0271193
mhi0812	-.0000266	.0000359	-0.74	0.464	-.0000997	.0000465
pownocc0812	.0257169	.0315132	0.82	0.421	-.0385547	.0899885
ppov0812	.0564012	.0259266	2.18	0.037	.0035235	.1092789
gentrification_status						
1	-10.6167	3.635173	-2.92	0.006	-18.03069	-3.20272
2	-1.084258	1.89973	-0.57	0.572	-4.958782	2.790267
3	-16.43663	4.982308	-3.30	0.002	-26.59812	-6.275148
5	-.5979455	1.968432	-0.30	0.763	-4.612588	3.416697
pMinority22	-.0244028	.046787	-0.52	0.606	-.1198256	.0710199
gentrification_status#c.pMinority22						
1	.1285897	.0510915	2.52	0.017	.024388	.2327914
2	.029657	.0317008	0.94	0.357	-.0349972	.0943112
3	.4020407	.1204424	3.34	0.002	.1563968	.6476847
5	.0231255	.0283716	0.82	0.421	-.0347388	.0809897
_cons	50.83631	16.9363	3.00	0.005	16.29449	85.37813

$$Food\ insecurity_{2022} = \beta0 + \beta1 * MedAge_{08-12} + \beta2 * pWhitenh_{08-12} + \beta3 * pBlacknh_{08-12} + \beta4 * pAsiannh_{08-12} + \beta5 * pLatino_{08-12} + \beta6 * pBachup_{08-12} + \beta7 * MHI_{08-12} + \beta8 * pOwnOcc_{08-12} + \beta9 * pPov_{08-12} + \beta10 * GentrificationStatus * pMinority_{2022} + \epsilon$$

```
Linear regression                               Number of obs     =         50
                                                F(16, 31)         =          .
                                                Prob > F          =          .
                                                R-squared         =     0.9032
                                                Root MSE          =      3.156
```

newfoodins	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
medage0812	.0717493	.129128	0.56	0.582	-.191609	.3351077
pwhitenh0812	-.2243254	.3215159	-0.70	0.491	-.8800614	.4314106
pblacknh0812	-.2230966	.3433058	-0.65	0.521	-.9232734	.4770802
pasiannh0812	-.2324489	.3871957	-0.60	0.553	-1.02214	.557242
platino0812	-.1621041	.3380358	-0.48	0.635	-.8515327	.5273245
pbachup0812	-.198328	.066091	-3.00	0.005	-.3331216	-.0635345
mhi0812	-.0000201	.00007	-0.29	0.776	-.0001628	.0001227
pownocc0812	-.0797892	.0609367	-1.31	0.200	-.2040704	.044492
ppov0812	.1812468	.0676709	2.68	0.012	.0432311	.3192625
gentrification_status						
1	-13.43489	8.535048	-1.57	0.126	-30.84223	3.972459
2	4.30133	4.45078	0.97	0.341	-4.776096	13.37876
3	30.61723	12.75459	2.40	0.023	4.604072	56.63039
5	1.613248	3.727127	0.43	0.668	-5.988278	9.214775
pMinority22	.1776561	.0754028	2.36	0.025	.0238711	.3314412
gentrification_status#c.pMinority22						
1	.1194589	.1232042	0.97	0.340	-.1318176	.3707355
2	-.1104764	.083567	-1.32	0.196	-.2809124	.0599597
3	-.8249802	.2933717	-2.81	0.008	-1.423316	-.2266448
5	-.0097117	.0569434	-0.17	0.866	-.1258486	.1064252
_cons	34.0514	35.59211	0.96	0.346	-38.53919	106.642

$$Lack\ of\ social\ or\ emotional\ support_{2022} = \beta 0 + \beta 1 * MedAge_{08-12} + \beta 2 * pWhitenh_{08-12} + \beta 3 * pBlacknh_{08-12} + \beta 4 * pAsiannh_{08-12} + \beta 5 * pLatino_{08-12} + \beta 6 * pBachup_{08-12} + \beta 7 * MHI_{08-12} + \beta 8 * pOwnOcc_{08-12} + \beta 9 * pPov_{08-12} + \beta 10 * GentrificationStatus * pMinority_{2022} + \epsilon$$

Linear regression

Number of obs	=	50
F(16, 31)	=	.
Prob > F	=	.
R-squared	=	0.8535
Root MSE	=	1.6849

newlackofsupport	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
medage0812	-.058729	.0588762	-1.00	0.326	-.1788077	.0613498
pwhitenh0812	-.0869367	.1104218	-0.79	0.437	-.3121435	.1382701
pblacknh0812	-.1297634	.1076555	-1.21	0.237	-.3493283	.0898015
pasiannh0812	-.1151363	.1249682	-0.92	0.364	-.3700106	.1397381
platino0812	-.1280654	.1113284	-1.15	0.259	-.3551211	.0989902
pbachup0812	-.0546844	.0260814	-2.10	0.044	-.1078777	-.0014911
mhi0812	-.0000495	.0000375	-1.32	0.197	-.0001261	.0000271
pownocc0812	.0203344	.030896	0.66	0.515	-.0426783	.0833471
ppov0812	.0373408	.0490553	0.76	0.452	-.0627082	.1373897
gentrification_status						
1	-5.520467	4.99921	-1.10	0.278	-15.71642	4.675489
2	.8750756	2.251948	0.39	0.700	-3.717802	5.467953
3	4.563113	7.324733	0.62	0.538	-10.37578	19.502
5	3.825562	2.45032	1.56	0.129	-1.171898	8.823023
pMinority22	.1774004	.0353948	5.01	0.000	.1052122	.2495885
gentrification_status#c.pMinority22						
1	.0501875	.0683097	0.73	0.468	-.089131	.189506
2	-.0224845	.0388227	-0.58	0.567	-.1016639	.0566949
3	-.1309991	.1710956	-0.77	0.450	-.4799509	.2179528
5	-.0619516	.0402003	-1.54	0.133	-.1439405	.0200374
_cons	32.34752	12.47258	2.59	0.014	6.909526	57.78551

$$Binge\ drinking_{2022} = \beta0 + \beta1 * MedAge_{08-12} + \beta2 * pWhitenh_{08-12} + \beta3 * pBlacknh_{08-12} + \beta4 * pAsiannh_{08-12} + \beta5 * pLatino_{08-12} + \beta6 * pBachup_{08-12} + \beta7 * MHI_{08-12} + \beta8 * pOwnOcc_{08-12} + \beta9 * pPov_{08-12} + \beta10 * GentrificationStatus * pMinority_{2022} + \epsilon$$

Linear regression		
Number of obs	=	50
F(16, 31)	=	.
Prob > F	=	.
R-squared	=	0.9108
Root MSE	=	1.1282

newbingedrink	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
medage0812	-.2640245	.0600419	-4.40	0.000	-.3864807	-.1415683
pwhitenh0812	.020565	.0966294	0.21	0.833	-.1765119	.2176419
pblacknh0812	-.0405802	.0972728	-0.42	0.679	-.2389694	.157809
pasiannh0812	-.0666565	.1091835	-0.61	0.546	-.2893377	.1560248
platino0812	.0041341	.0918493	0.05	0.964	-.1831938	.191462
pbachup0812	.0441417	.0235135	1.88	0.070	-.0038144	.0920978
mhi0812	.000069	.0000316	2.18	0.037	4.49e-06	.0001335
pownocc0812	-.0140961	.0241165	-0.58	0.563	-.063282	.0350899
ppov0812	-.0302939	.0220295	-1.38	0.179	-.0752233	.0146356
gentrification_status						
1	-4.553173	5.765109	-0.79	0.436	-16.31119	7.204844
2	1.281096	1.820073	0.70	0.487	-2.430966	4.993159
3	-29.01559	4.259536	-6.81	0.000	-37.70297	-20.32821
5	1.88535	1.675015	1.13	0.269	-1.530865	5.301565
pMinority22	-.0001796	.0322339	-0.01	0.996	-.0659211	.065562
gentrification_status#c.pMinority22						
1	.0715588	.0716235	1.00	0.325	-.0745184	.217636
2	-.0017485	.0292486	-0.06	0.953	-.0614015	.0579045
3	.6737549	.0992104	6.79	0.000	.4714138	.8760959
5	-.0244499	.024959	-0.98	0.335	-.0753542	.0264544
_cons	24.54161	10.66124	2.30	0.028	2.797879	46.28535

$$Short\ sleep_{2022} = \beta 0 + \beta 1 * MedAge_{08-12} + \beta 2 * pWhitenh_{08-12} + \beta 3 * pBlacknh_{08-12} + \beta 4 * pAsiannh_{08-12} + \beta 5 * pLatino_{08-12} + \beta 6 * pBachup_{08-12} + \beta 7 * MHI_{08-12} + \beta 8 * pOwnOcc_{08-12} + \beta 9 * pPov_{08-12} + \beta 10 * GentrificationStatus * pMinority_{2022} + \epsilon$$

Linear regression

Number of obs	=	50
F(16, 31)	=	.
Prob > F	=	.
R-squared	=	0.9228
Root MSE	=	1.242

newshortsleep	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
medage0812	-.0389505	.0528204	-0.74	0.466	-.1466784	.0687774
pwhitenh0812	-.0852167	.1058151	-0.81	0.427	-.3010281	.1305946
pblacknh0812	-.0396081	.1029699	-0.38	0.703	-.2496167	.1704005
pasiannh0812	-.0730583	.1243665	-0.59	0.561	-.3267055	.1805888
platino0812	-.0817807	.1021198	-0.80	0.429	-.2900553	.1264939
pbachup0812	-.0572781	.0252448	-2.27	0.030	-.1087653	-.0057909
mhi0812	-.0000231	.0000291	-0.79	0.433	-.0000824	.0000362
pownocc0812	.0289035	.0221925	1.30	0.202	-.0163583	.0741653
ppov0812	.0501385	.0226183	2.22	0.034	.0040082	.0962688
gentrification_status						
1	1.653013	2.964408	0.56	0.581	-4.392938	7.698964
2	-.0441273	1.791019	-0.02	0.981	-3.696935	3.60868
3	5.25796	5.224635	1.01	0.322	-5.397754	15.91367
5	1.246099	1.881899	0.66	0.513	-2.592059	5.084257
pMinority22	.0927444	.0297979	3.11	0.004	.0319711	.1535176
gentrification_status#c.pMinority22						
1	-.04228	.041466	-1.02	0.316	-.1268505	.0422905
2	-.0022963	.0301243	-0.08	0.940	-.0637351	.0591426
3	-.140498	.1217331	-1.15	0.257	-.3887743	.1077784
5	-.0127118	.0264694	-0.48	0.634	-.0666964	.0412729
_cons	38.44188	11.52428	3.34	0.002	14.93796	61.9458

$$Fair\ or\ poor\ srh_{2022} = \beta 0 + \beta 1 * MedAge_{08-12} + \beta 2 * pWhitenh_{08-12} + \beta 3 * pBlacknh_{08-12} + \beta 4 * pAsiannh_{08-12} + \beta 5 * pLatino_{08-12} + \beta 6 * pBachup_{08-12} + \beta 7 * MHI_{08-12} + \beta 8 * pOwnOcc_{08-12} + \beta 9 * pPov_{08-12} + \beta 10 * GentrificationStatus * pMinority_{2022} + \epsilon$$

Linear regression

Number of obs	=	50
F(16, 31)	=	.
Prob > F	=	.
R-squared	=	0.9085
Root MSE	=	2.1295

newfairorpoorsrh	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
medage0812	.1347452	.1133673	1.19	0.244	-.096469	.3659594
pwhitenh0812	-.1800131	.175104	-1.03	0.312	-.5371401	.1771139
pblacknh0812	-.1523076	.1811521	-0.84	0.407	-.5217698	.2171546
pasiannh0812	-.1273917	.2062248	-0.62	0.541	-.54799	.2932066
platino0812	-.0869396	.1766668	-0.49	0.626	-.4472539	.2733748
pbachup0812	-.1650789	.0451943	-3.65	0.001	-.2572534	-.0729045
mhi0812	-.0000667	.000055	-1.21	0.235	-.0001789	.0000455
pownocc0812	.0005101	.0417993	0.01	0.990	-.0847402	.0857604
ppov0812	.056189	.0473568	1.19	0.244	-.0403959	.1527739
gentrification_status						
1	-2.044337	6.825766	-0.30	0.767	-15.96558	11.87691
2	-1.184721	4.055297	-0.29	0.772	-9.455555	7.086112
3	37.1819	10.86995	3.42	0.002	15.01249	59.35131
5	-2.068305	3.044004	-0.68	0.502	-8.276593	4.139982
pMinority22	.0207857	.0629505	0.33	0.743	-.1076027	.1491742
gentrification_status#c.pMinority22						
1	-.0009369	.0946805	-0.01	0.992	-.1940389	.1921652
2	-.0091426	.0717003	-0.13	0.899	-.1553763	.137091
3	-.8470916	.247269	-3.43	0.002	-1.3514	-.3427832
5	.0463344	.0475591	0.97	0.337	-.0506631	.1433319
_cons	34.09438	21.06946	1.62	0.116	-8.877071	77.06583

$$Routine\ doctor\ visits_{2022} = \beta 0 + \beta 1 * MedAge_{08-12} + \beta 2 * pWhitenh_{08-12} + \beta 3 * pBlacknh_{08-12} + \beta 4 * pAsiannh_{08-12} + \beta 5 * pLatino_{08-12} + \beta 6 * pBachup_{08-12} + \beta 7 * MHI_{08-12} + \beta 8 * pOwnOcc_{08-12} + \beta 9 * pPov_{08-12} + \beta 10 * GentrificationStatus * pMinority_{2022} + \epsilon$$

Linear regression			
	Number of obs	=	50
	F(16, 31)	=	.
	Prob > F	=	.
	R-squared	=	0.9423
	Root MSE	=	1.0155

newdocvisits	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
medage0812	.307489	.0591081	5.20	0.000	.1869371	.4280408
pwhitenh0812	.0306314	.0830212	0.37	0.715	-.1386914	.1999542
pblacknh0812	.1542389	.07572	2.04	0.050	-.0001931	.308671
pasiannh0812	.0700122	.0868581	0.81	0.426	-.107136	.2471604
platino0812	.0386104	.0748214	0.52	0.609	-.1139888	.1912096
pbachup0812	-.022442	.0207249	-1.08	0.287	-.0647106	.0198267
mhi0812	-.000041	.0000259	-1.59	0.123	-.0000938	.0000117
pownocc0812	.0207074	.0207391	1.00	0.326	-.0215903	.0630052
ppov0812	.0063181	.0244749	0.26	0.798	-.0435988	.056235
gentrification_status						
1	5.11456	4.63851	1.10	0.279	-4.345743	14.57486
2	.2341625	1.795055	0.13	0.897	-3.426876	3.895201
3	19.63775	4.157836	4.72	0.000	11.15779	28.11771
5	-.2775684	1.606651	-0.17	0.864	-3.554355	2.999218
pMinority22	-.0538468	.0401385	-1.34	0.189	-.1357097	.0280162
gentrification_status#c.pMinority22						
1	-.0698161	.0582139	-1.20	0.239	-.1885441	.048912
2	-.0197134	.0272895	-0.72	0.475	-.0753708	.0359439
3	-.4749196	.0996316	-4.77	0.000	-.6781195	-.2717196
5	-.0018899	.0243054	-0.08	0.939	-.0514611	.0476813
_cons	64.99213	11.20415	5.80	0.000	42.14111	87.84316

$$Mental\ distress_{2022} = \beta 0 + \beta 1 * MedAge_{08-12} + \beta 2 * pWhitenh_{08-12} + \beta 3 * pBlacknh_{08-12} + \beta 4 * pAsiannh_{08-12} + \beta 5 * pLatino_{08-12} + \beta 6 * pBachup_{08-12} + \beta 7 * MHI_{08-12} + \beta 8 * pOwnOcc_{08-12} + \beta 9 * pPov_{08-12} + \beta 10 * GentrificationStatus * pMinority_{2022} + \epsilon$$

Linear regression

Number of obs	=	50
F(16, 31)	=	.
Prob > F	=	.
R-squared	=	0.8165
Root MSE	=	1.9413

newmentaldistress	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
medage0812	-.4142549	.0966594	-4.29	0.000	-.6113931	-.2171167
pwhitenh0812	-.1288899	.2162322	-0.60	0.555	-.5698983	.3121185
pblacknh0812	-.2061484	.2028059	-1.02	0.317	-.6197738	.2074771
pasiannh0812	-.2702612	.2380458	-1.14	0.265	-.7557588	.2152364
platino0812	-.2125732	.2022335	-1.05	0.301	-.6250312	.1998848
pbachup0812	-.0757099	.0469484	-1.61	0.117	-.1714617	.0200419
mhi0812	-.0000584	.0000519	-1.13	0.269	-.0001643	.0000475
pownocc0812	.050206	.0454052	1.11	0.277	-.0423986	.1428106
ppov0812	.0835488	.0404194	2.07	0.047	.0011128	.1659848
gentrification_status						
1	-12.54312	4.435802	-2.83	0.008	-21.58999	-3.496238
2	-1.947346	2.519735	-0.77	0.445	-7.08638	3.191687
3	-18.86272	7.434878	-2.54	0.016	-34.02625	-3.699188
5	-.2414194	2.832186	-0.09	0.933	-6.017702	5.534863
pMinority22	.0341368	.0603238	0.57	0.576	-.0888945	.1571681
gentrification_status#c.pMinority22						
1	.1442224	.0631862	2.28	0.029	.0153533	.2730915
2	.041281	.0447802	0.92	0.364	-.0500489	.1326109
3	.439383	.1774254	2.48	0.019	.0775216	.8012444
5	.0209358	.0414972	0.50	0.617	-.0636983	.1055698
_cons	49.41838	24.8733	1.99	0.056	-1.311045	100.1478

$$Socially\ isolated_{2022} = \beta 0 + \beta 1 * MedAge_{08-12} + \beta 2 * pWhitenh_{08-12} + \beta 3 * pBlacknh_{08-12} + \beta 4 * pAsiannh_{08-12} + \beta 5 * pLatino_{08-12} + \beta 6 * pBachup_{08-12} + \beta 7 * MHI_{08-12} + \beta 8 * pOwnOcc_{08-12} + \beta 9 * pPov_{08-12} + \beta 10 * GentrificationStatus * pMinority_{2022} + \epsilon$$

```
Linear regression                               Number of obs     =         50
                                                F(16, 31)         =          .
                                                Prob > F          =          .
                                                R-squared         =     0.8627
                                                Root MSE          =      1.511
```

newsociallyisolated	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
medage0812	-.3284785	.0642093	-5.12	0.000	-.4594342	-.1975229
pwhitenh0812	-.034227	.1314072	-0.26	0.796	-.3022337	.2337797
pblacknh0812	-.1320157	.1233913	-1.07	0.293	-.3836739	.1196424
pasiannh0812	-.1702666	.1447069	-1.18	0.248	-.4653982	.124865
platino0812	-.1303855	.1277766	-1.02	0.315	-.3909876	.1302166
pbachup0812	-.0275425	.0298896	-0.92	0.364	-.0885027	.0334177
mhi0812	-.0000281	.0000371	-0.76	0.454	-.0001038	.0000475
pownocc0812	.0144009	.0319083	0.45	0.655	-.0506765	.0794783
ppov0812	.0584649	.0413214	1.41	0.167	-.0258105	.1427404
gentrification_status						
1	-11.46989	3.96175	-2.90	0.007	-19.54993	-3.389848
2	1.069125	1.983937	0.54	0.594	-2.977141	5.115391
3	-20.1476	6.621297	-3.04	0.005	-33.65182	-6.643374
5	2.677264	2.387413	1.12	0.271	-2.191898	7.546425
pMinority22	.1291245	.038493	3.35	0.002	.0506175	.2076315
gentrification_status#c.pMinority22						
1	.1321136	.0538149	2.45	0.020	.0223575	.2418697
2	-.0085958	.0339485	-0.25	0.802	-.0778342	.0606427
3	.4407404	.1558091	2.83	0.008	.1229656	.7585153
5	-.0363918	.0382968	-0.95	0.349	-.1144987	.041715
_cons	49.80234	15.45671	3.22	0.003	18.27816	81.32651

$$Percent\ minority_{2022} = \beta 0 + \beta 1 * MedAge_{08-12} + \beta 2 * pWhitenh_{08-12} + \beta 3 * pBlacknh_{08-12} + \beta 4 * pAsiannh_{08-12} + \beta 5 * pLatino_{08-12} + \beta 6 * pBachup_{08-12} + \beta 7 * MHI_{08-12} + \beta 8 * pOwnOcc_{08-12} + \beta 9 * pPov_{08-12} + \beta 10 * GentrificationStatus + \epsilon$$

```
. regress pMinority22 medage0812 pwhitenh0812 pblacknh0812 pasiannh0812 platino0812 pbachup0812 mhi0812 pownocc0812 ppov0812 ib4.gentrificat
> ion_status, robust

Linear regression                               Number of obs     =         50
                                                F(13, 36)         =      79.70
                                                Prob > F          =     0.0000
                                                R-squared         =     0.9137
                                                Root MSE          =     6.6213
```

pMinority22	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
medage0812	-.6540075	.2308826	-2.83	0.008	-1.122259	-.185756
pwhitenh0812	-1.060608	.5789871	-1.83	0.075	-2.234848	.1136324
pblacknh0812	-.4343141	.5904522	-0.74	0.467	-1.631807	.7631786
pasiannh0812	-.6611045	.6610669	-1.00	0.324	-2.00181	.6796013
platino0812	-.4958589	.5788138	-0.86	0.397	-1.669748	.67803
pbachup0812	-.3088704	.0890311	-3.47	0.001	-.4894339	-.128307
mhi0812	-.000116	.0001504	-0.77	0.446	-.0004211	.0001891
pownocc0812	-.0134717	.1095179	-0.12	0.903	-.2355843	.208641
ppov0812	-.2065487	.1950192	-1.06	0.297	-.6020659	.1889685
gentrification_status						
1	2.811429	4.542179	0.62	0.540	-6.400538	12.0234
2	-1.25184	3.208078	-0.39	0.699	-7.758123	5.254444
3	-7.775476	6.276346	-1.24	0.223	-20.50449	4.953544
5	4.706877	2.598741	1.81	0.078	-.5636147	9.977368
_cons	175.869	65.55126	2.68	0.011	42.9249	308.8131

$$Percent\ Black_{2022} = \beta 0 + \beta 1 * MedAge_{08-12} + \beta 2 * pWhitenh_{08-12} + \beta 3 * pBlacknh_{08-12} + \beta 4 * pAsiannh_{08-12} + \beta 5 * pLatino_{08-12} + \beta 6 * pBachup_{08-12} + \beta 7 * MHI_{08-12} + \beta 8 * pOwnOcc_{08-12} + \beta 9 * pPov_{08-12} + \beta 10 * GentrificationStatus + \epsilon$$

```
. regress pBlack22 medage0812 pwhitenh0812 pblacknh0812 pasiannh0812 platino0812 pbachup0812 mhi0812 pownocc0812 ppov0812 ib4.gentrification_
> status, robust

Linear regression                               Number of obs     =         50
                                                F(13, 36)         =      52.63
                                                Prob > F          =     0.0000
                                                R-squared         =     0.9450
                                                Root MSE          =     5.7004
```

pBlack22	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
medage0812	-.2264824	.2313341	-0.98	0.334	-.6956496	.2426848
pwhitenh0812	-.2332707	.4194828	-0.56	0.582	-1.084021	.6174799
pblacknh0812	.6540928	.4336983	1.51	0.140	-.2254882	1.533674
pasiannh0812	-.1315094	.476655	-0.28	0.784	-1.098211	.8351917
platino0812	-.2729304	.4343267	-0.63	0.534	-1.153786	.607925
pbachup0812	-.0915352	.0680764	-1.34	0.187	-.2296005	.0465301
mhi0812	.0000682	.0001368	0.50	0.621	-.0002092	.0003457
pownocc0812	-.0625687	.0869559	-0.72	0.476	-.2389234	.1137859
ppov0812	-.1623833	.1607416	-1.01	0.319	-.4883823	.1636158
gentrification_status						
1	1.012145	3.621798	0.28	0.781	-6.333202	8.357492
2	.5142154	2.678736	0.19	0.849	-4.918512	5.946943
3	-6.793461	5.274621	-1.29	0.206	-17.49089	3.903967
5	4.195055	2.837312	1.48	0.148	-1.559281	9.949392
_cons	37.01149	47.11411	0.79	0.437	-58.54036	132.5633