ABSTRACT

CHAKRAVARTY, ADITI. An Analysis of Environmental Gentrification Indicators and Brownfields Redevelopment in Raleigh, North Carolina. (Under the direction of Dr. Jennifer Richmond-Bryant).

This study examines the social impacts of brownfields redevelopment in Raleigh, North Carolina, with a particular focus on indicators of gentrification and neighborhood change surrounding sites enrolled in the state's Brownfields Redevelopment Program. Administered by the North Carolina Department of Environmental Quality (NCDEQ), this program facilitates the cleanup and reuse of contaminated properties, often abandoned or underutilized, by offering environmental liability relief and tax incentives through Brownfields Agreements. As North Carolina's urban centers such as Raleigh, Charlotte, and Wilmington experience rapid economic growth and real estate investment, many brownfields sites located in historically disinvested and marginalized communities are increasingly subject to redevelopment pressure.

While the North Carolina Brownfields Property Reuse Act of 1997 was originally intended to spur economic revitalization and public health improvements in underserved areas, literature suggests that such efforts may accelerate neighborhood gentrification and residential displacement. This study aims to evaluate whether redevelopment near brownfields sites in Raleigh, NC, correlates with changes in demographic, housing, and socioeconomic characteristics that reflect gentrification dynamics. Using geospatial and statistical analysis, brownfield data from NCDEQ and demographic data from American Community Survey (ACS) 5-year estimates are analyzed to assess the environmental justice implications of brownfields reuse. Findings from this study seek to inform equitable redevelopment policy and advance understanding of how environmental remediation intersects with patterns of urban inequality.

An Analysis of Environmental Gentrification Indictors and Brownfields Redevelopment in Raleigh, North Carolina.

by
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BIOGRAPHY

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CHAPTER 1. INTRODUCTION

Urban communities in the United States often carry industrial histories that are the source of present-day hazardous waste and contaminant impacts for surrounding neighborhoods (Bihari et al.; 2023; Datko-Williams et al., 2014). Common pollutants such as petroleum, heavy metals, and volatile organic compounds, can be released into soil, groundwater and/or air by industrial operators and continue to impact the environment for decades or even centuries after being emitted, persisting long after the polluting facility has been decommissioned or relocated (Sanchez et al., 2017). The long-term environmental and public health impacts from these polluting facilities are referred to as legacy pollution and have been found to disproportionately impact low-income communities and communities of color (Pinderhughes, 1996; Brulle and Pellow, 2006; Mohai and Saha, 2007; Wolverton, 2009; Eckerd and Keeler, 2012; Sanchez et al., 2017).

Neighborhoods composed primarily of people of color and/or low-income neighborhoods have historically endured the greatest impacts from hazardous sites and legacy pollution (Pinderhughes, 1996; Brulle and Pellow, 2006; Mohai and Saha, 2007; Wolverton, 2009; Eckerd and Keeler, 2012; Sanchez, 2017). Industries looked to minimize production costs by selecting areas where land values and operation costs would be low, while communities surrounding these areas generally lacked the social capital and political power to influence the development or relocation of industrial projects proximate to their residences (Mohai and Saha, 2007; Wolverton, 2009). A prominent example of social inequality and hazardous waste siting can be found in the case of Warren County, North Carolina in 1982 when African American residents led protests

over the disposal of PCB-contaminated soils near their community, which served as a critical flashpoint for the environmental justice movement and environmental justice as a research discipline (Sanchez 2017 et al.; Pinderhughes 1996; Agyeman 2002). The resulting body of literature revealed that race was a key predictor in the placement of environmentally hazardous facilities and that communities with multiple hazardous waste facilities have on average a minority population percentage three times higher than those without facilities (Commission for Racial Justice 1987; Brulle and Pellow, 2006; Sanchez 2017). The persistence of lead contamination in urban soils exemplifies the long-term consequences of legacy pollution and environmental justice. Despite the nationwide decline in airborne lead emissions following the phase-out of leaded gasoline in 1995, soil lead levels remain disproportionately high in densely populated, low-income, and minority neighborhoods (Datko-Williams et al. 2014).

Sites with complex environmental histories are challenging from both a public health and reuse standpoint, because these sites can be a source of property devaluation as well as contaminant exposure, particularly in urban landscapes where population density is greater (Eckerd and Keeler, 2012; Lee and Mohai, 2013). To incentivize the cleanup and reuse of overlooked sites and encourage community driven planning and investment, the US Environmental Protection Agency (EPA) provides federal funding for properties that qualify as a Brownfields Property, which is defined as "real property, the expansion, redevelopment, or reuse of which may be complicated by the presence or potential presence of a hazardous substance, pollutant, or contaminant" by Public Law 107-188 (H.R. 2869) - "Small Business Liability Relief and Brownfields Revitalization Act" (the "Brownfields Law") signed into federal law January 11, 2002 (Sullivan, 2017). Federal funding through this program can be used for planning,

assessment, and cleanup activities at sites that meet this definition, with an end-goal of putting these sites back into productive use (U.S. EPA, 2024). Brownfields sites can also be enrolled into the state voluntary cleanup action program, which can vary programmatically due to differing state statutes.

The origin of EPA's Brownfield Revitalization Grant Program can be traced back to the 1978 environmental disaster at Love Canal, where a working-class neighborhood was built atop toxic industrial waste. Identification and publicity of this situation led to the passage of the Comprehensive Environmental Response, Compensation, and Liability Act (CERCLA) of 1980 most commonly known as "Superfund", to regulate hazardous waste sites and fund cleanup efforts. However, CERCLA's liability provisions deterred investment in contaminated land, prompting a policy shift in the 1990s toward remediation and redevelopment. The term "brownfields" was introduced, and new federal programs, including the Brownfield Revitalization Program, offered financial incentives for cleanup. The 2002 CERCLA amendment officially known as the Small Business Liability Relief and Brownfields Revitalization Act clarified liability protections for landowners who were found to not have caused or contributed to contamination, encouraging redevelopment efforts (Small Business Liability Relief and Brownfields Revitalization Act, 2002).

Many brownfield sites are located in or near historically disinvested neighborhoods, often communities of color or low-income areas, that have borne the brunt of environmental degradation, poor land use planning, and industrial abandonment (Pinderhughes, 1996; Mohai and Saha, 2006; Wolverton, 2009; Eckerd and Keeler, 2012; Sanchez, 2017). As such,

brownfields redevelopment holds the potential to address long-standing environmental injustices by eliminating hazardous exposures, removing urban blight, and enhancing environmental health. These efforts can lead to improved public health outcomes, such as reduced rates of asthma and pollution-related illnesses, which disproportionately affect marginalized population (Brulle and Pellow, 2006; Wolverton, 2009).

However, without equitable planning and inclusive engagement, redevelopment can also lead to consequences such as gentrification and the displacement of existing residents (Mohai and Saha 2006; Beccera, 2022). Rising property values and rents, while beneficial to the local tax base, can strain long-term residents' ability to remain in place, particularly for renters and low-income homeowners (O'Leary et al., 2023). These outcomes are especially concerning in communities defined by heightened vulnerability which, in the context of assessing redevelopment impacts, reflects the degree to which communities are negatively affected by exposure to social and environmental stressors and limited in their capacity to adapt (Pearsall, 2010). Therefore, while the economic and environmental benefits of brownfields redevelopment are clear, ensuring that these benefits are equitably distributed is critical. Community-driven redevelopment strategies, affordable housing preservation, and anti-displacement policies are critical to ensuring that the revitalization of brownfields truly serve the communities most impacted by their legacy (Pulido et al., 2016).

Recent decades have yielded rapid growth in US cities, surpassing growth in other areas of the country, resulting in greater demand for urban housing and for "greener" cities (Beccera, 2022). This trend is especially evident in the southeastern United States, which experienced significant

population gains from domestic migration in 2019, in contrast to population losses in the Northeast and Midwest (Kerns-D'Amore et al., 2023). As urban areas expand, underutilized or contaminated land, such as brownfields, presents both a challenge and opportunity for sustainable development. Land cleanup and redevelopment for various uses, such as commercial, residential, or recreational, also has significant fiscal advantages for local and state governments. According to a 2010 survey by the US Conference of Mayors, 85% of 150 cities identified tax base growth as a key benefit of redeveloping brownfields (Sullivan, 2017; US Conference of Mayors, 2010). Cleanup efforts can boost local tax revenues by returning abandoned properties to the tax rolls and increasing the value of nearby properties. Additionally, redevelopment can drive economic activity, such as new business, higher employment, and increased consumer spending, which can boost state income and sales tax revenues. These additional funds allow municipalities to improve public services and education for local communities (Sullivan, 2017; US EPA, 2024).

The State of North Carolina is no exception when it comes to supporting efforts that will ultimately increase tax revenue. As North Carolina continues to experience population growth and rising investment in the redevelopment of historically industrial properties, the voluntary cleanup action program known as the North Carolina Brownfields Section (NCBRS) within the North Carolina Department of Environmental Quality (NCDEQ) continues to grow rapidly in number of eligible brownfields properties.

Raleigh, the capital of North Carolina, has a complex history shaped by patterns of racial segregation, industrial growth, and suburban expansion. Historically, many Black and low-

income communities in Raleigh were relegated to industrial corridors and flood-prone areas due to discriminatory land use policies and redlining (Green, n.d.). These areas often housed manufacturing, warehousing, and rail-related infrastructure, leaving a legacy of contaminated and underutilized land (Anderson et al, 2003). Former textile mills, dry cleaners, auto repair shops, and fuel storage facilities are examples of the types of industries that have contributed to the environmental degradation now targeted under brownfields programs (North Carolina Department of Environmental Quality [NCDEQ] Success Stories, 2025). At the same time, Raleigh's population has grown rapidly, particularly since the 1990s, as part of the broader expansion of the Research Triangle region (Wake County Government Population Trends, 2025). This growth has intensified development pressures and increased the value of underutilized urban land in proximity to downtown and transit corridors. Many of these sites are located within historically Black and working-class neighborhoods, which now face the dual pressures of disinvestment legacy and market-driven gentrification (Green, n.d.; Anderson et al., 2003)

Raleigh's development has followed a pattern of urban revitalization and infill, often targeting vacant or industrial parcels for mixed-use and residential redevelopment. The City has aligned these trends with state-level policies that offer tax incentives for brownfields redevelopment (North Carolina Department of Environmental Quality [NCDEQ] FAQs, 2025). The North Carolina Brownfields Redevelopment Section (NCBRS) provides liability protection and property tax exclusions for developers willing to invest in contaminated properties. One notable incentive includes a partial exclusion of increased property value from taxation for up to five years, intended to encourage redevelopment while mitigating financial risk for property owners.

These incentives have attracted private investment, particularly in neighborhoods adjacent to downtown Raleigh, but have also raised concerns about displacement and affordability. As land is cleaned and reinvested, communities historically burdened by environmental hazards may find themselves priced out of their neighborhoods (Pinderhughes, 1996; Mohai and Saha, 2006; Eckerd and Keeler, 2012; Sanchez et al., 2017).

The objective of this study is to evaluate the socioeconomic, demographic, and housing impacts of brownfield redevelopment on surrounding residential neighborhoods, with a specific focus on understanding whether such investments contribute to gentrification and displacement of communities of color and low-income populations in Raleigh, North Carolina. With the rise of brownfield redevelopment as a tool for urban revitalization, this study asks whether these efforts redress historical injustices or, conversely, contribute to new forms of inequity through gentrification and displacement. To further understand neighborhood changes proximate to Raleigh brownfields sites, GIS analysis was used to assess key indicators.

CHAPTER 2. METHODOLOGY

Data Sources

Geospatial analysis techniques and R analysis were applied to understand changes for selected characteristics at the block group level in residential neighborhoods within a specified radius of redeveloped brownfields Properties. Properties designated by the North Carolina Department of Environmental Quality (NCDEQ) as brownfields sites and assigned "recorded" status between 2010 and 2020 in Raleigh, NC were used for the scope of this analysis (North Carolina Department of Environmental Quality Online GIS. Accessed July 28, 2025). The period of time ranging from 2010 to 2020 is reflective of a strong real estate market and rapid urbanization within this region of North Carolina, conditions which are conducive to transactions involving environmentally contaminated land. The assignment of "recorded" status for a brownfields property is a regulatory endpoint indicating that the site has met the criteria to be considered safe for public use (North Carolina Department of Environmental Quality, Brownfields Projects Map Inventory, 2025).

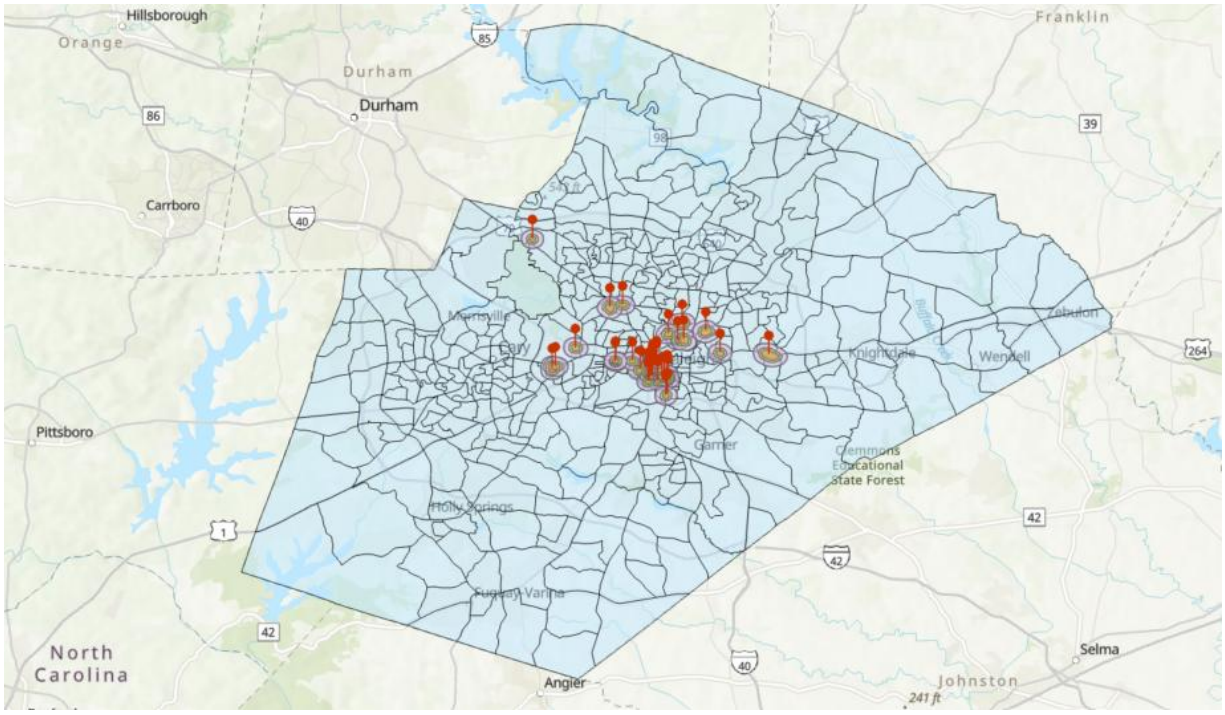

Figure 1. Brownfields Sites in Raleigh, NC

Data used for this analysis were accessed via NCDEQ's Open Data Portal, including the DEQ Division of Waste Management Brownfields Redevelopment Section database, and U.S Census Bureau's American Community Survey (ACS) (North Carolina Department of Environmental Quality Online GIS, 2024; U.S. Census Bureau, 2012; U.S. Census Bureau, 2022). The NCDEQ data were used to construct a GIS data layer of 42 recorded brownfields sites within the City of Raleigh. This layer was spatially overlaid with ACS demographic data at the block group level, which offers finer spatial resolution than census tracts and typically includes 600 to 3,000 residents. ACS 5-year estimates for 2008-2012 and 2018-2022 were used to approximate conditions around the 2010 and 2020 timepoints, respectively.

Analysis

To assess the population characteristics surrounding brownfields sites, buffer zones of 0.5 miles, 0.25 miles, and 0.125 miles were created around each site using GIS. The GIS apportionment tool was then employed to merge demographic indicators within these buffered areas. This approach follows distance-based methods developed by Mohai and Saha (2007), where population characteristics are weighted based on the proportion of each block group's area that falls within the specified buffer distances. This technique enables a more spatially precise analysis of communities potentially impacted by brownfields redevelopment. By using different buffer distances, we can gain a better understanding of how communities may be impacted by brownfields redevelopment and how close proximity correlates with vulnerability.

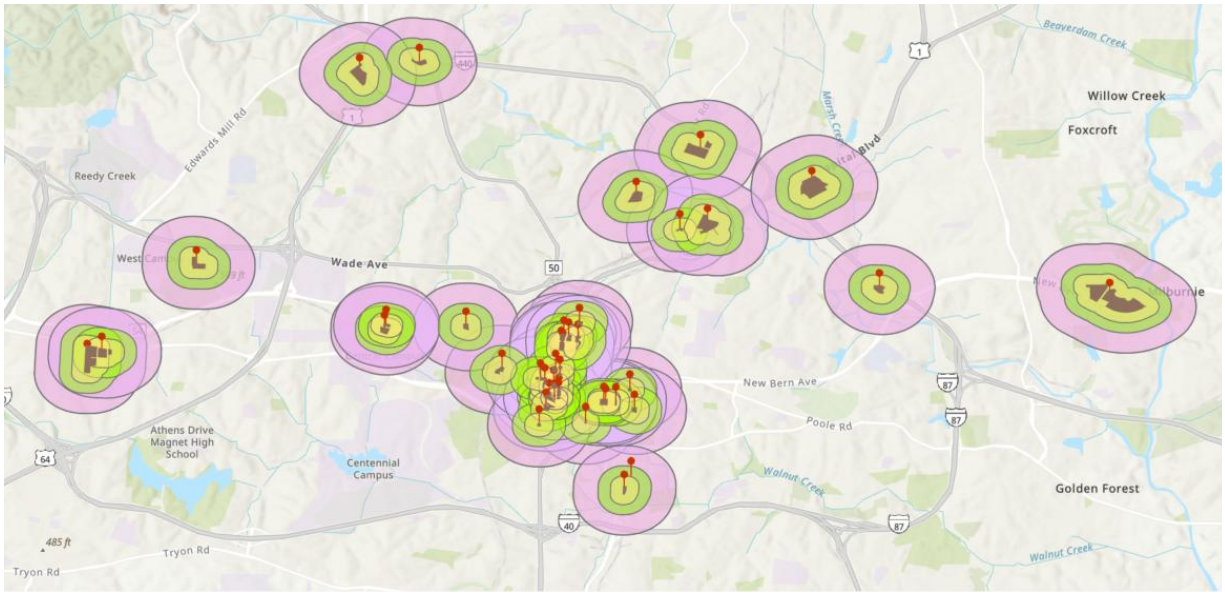

Figure 2. Buffer Zones for Raleigh Brownfields Sites

The indicators of interest in this study are grouped into three main categories: socioeconomic, housing, and demographic characteristics:

i. Socioeconomic indicators include median household income, the percentage of households living below the federal poverty line, and educational attainment levels (e.g., proportion of the population with less than a high school diploma or with a bachelor's degree or higher).

ii. Housing indicators focus on tenure status (owner-occupied vs. renter-occupied units), average or median home values, and the percentage of vacant housing units. These metrics help assess both housing market pressures and neighborhood stability.

iii. Demographic indicators include race/ethnicity and age distribution, which are critical for understanding the composition of communities most affected by brownfields and potential redevelopment impacts.

To evaluate the relationship between housing market changes and neighborhood composition, the following questions guide the quantitative analysis:

(1) Where rental values have tripled, what population shifts do we observe?
This question explores whether extreme rent increases are associated with demographic shifts, particularly in race, age, educational attainment, and poverty levels. A multivariate regression model was constructed to identify the predictors of rent tripling.

(2) Where rental values have remained stable, how do demographic patterns compare?

Here high-rent growth areas were compared to low-growth areas to identify contrasts in racial composition, income levels, poverty rates, and educational attainment. Regression models are applied to both 2010 and 2020 data, examining the statistical relationships between rental values and demographic indicators.

(3) Have housing values outpaced inflation, and if so, what indicators of displacement emerge? By adjusting housing values for inflation using national Consumer Price Index (CPI) data, this question identifies tracts where real housing costs have significantly increased. For those areas, the analysis investigates whether a growing disparity between housing values and household incomes is present.

CHAPTER 3. RESULTS AND DISCUSSION

An initial statistical comparison was performed across the three spatial buffer distances: 0.5 miles, 0.25 miles, and 0.125 miles. The multiple buffer sizes function as a quality assurance measure and aim to verify whether the analysis results are sensitive to the spatial scale of measurement. Because each smaller buffer is encompassed by the larger one, minimal variations across the buffer sizes would suggest that findings are not driven by the choice of radius. The results from the analysis show relatively stable trends, with only modest differences in key indicators such as income-to-housing ratios, educational attainment, and poverty levels. This consistency reinforces the overall reliability of the observed patterns and strengthens confidence in the broader conclusions of the analysis. The convergence of findings across buffer sizes suggests that the associations and trends identified are not singularly dependent on the specific spatial extent selected but rather reflect socio-economic dynamics present in the area.

The results seen in Table 1 were assessed for significance using an adjusted p-value threshold of 0.0015 to account for 32 comparisons, as well as a conventional threshold of 0.05 to identify marginal trends.

Table 1. Comparisons Across Buffer Sizes for All Indicators

Buffer Size	Number of Significant Comparisons ($p < 0.0015$)	Number of Marginally Significant Comparisons ($p < 0.05$)
0.5	24	28
0.25	19	27
0.125	17	25

The 0.5-mile buffer zone exhibits the highest number of statistically significant comparisons, which indicates that broader neighborhood-level impacts of brownfields redevelopment may be more detectable at this spatial scale. While the 0.25 miles and 0.125-mile buffers also show significant results, the variations across the buffer sizes potentially reflect the spatial heterogeneity of demographic changes and the varying intensity of redevelopment effects within proximity. The slightly lower significance counts at the smallest buffer of 0.125 miles may be due to the limited population size or higher variability in a smaller geographic area.

Housing and Inflation

A deeper look into rent and housing can give some insight into how proximity to brownfields redevelopment may be associated with housing pressures or displacement risk. Affordability metrics were aggregated across buffer zones and summarized in Table 2.

Table 2. Affordability Metrics for Housing and Inflation Indicators

Buffer Size	Rent Tripled (%)	Rent Astronomical (%)	Housing Outpaced (%)
0.5	46	17	9.7
0.25	41	0	15
0.125	44	0	17

Census block groups where median gross rent in 2020 was at least three times higher than in 2010 were flagged, identifying locations undergoing rapid rent increases and potentially indicating displacement pressures. Within the 0.5-mile radius, 46% of block groups experienced a tripling of median rent from 2010 to 2020, which is slightly higher than the rent tripling statistics for the 0.25-mile and 0.125-mile buffer. In contrast, astronomically high 2020 rents, which accounts for the top 5% of 2020 median gross rents, were only identified within the 0.5-

mile buffer. Its absence at smaller buffers may indicate that these outlier increases occur at a broader neighborhood level rather than right at the core of redevelopment areas, possibly due to general neighborhood gentrification (Pearsall, 2010; Lee and Mohai, 2012).

Housing values outpacing inflation were compared across time. If 2020 values increased more than 20% over 2010 values (the approximate rate of inflation over the decade), the area was flagged for above-inflation appreciation (U.S Bureau of Labor Statistics, 2010; U.S Bureau of Labor Statistics, 2020). Sigificantly, the 0.125-mile buffer shows the highest rate of housing value growth exceeding inflation, with 17% of block groups surpassing the 20% national inflation benchmark, and the 0.5-mile buffer shows fewer cases of housing values outpacing inflation at 9.8%, despite the highest rent escalation being attributed to this buffer. This suggests that rent may be more sensitive than ownership values within the inner zones, or that renters may be absorbing disproportionate cost burdens.

Demographic Patterns

To assess the demographic patterns associated with rent changes near brownfields sites in Raleigh, we first calculated a rent ratio, defined as the 2020 median rent divided by the 2010 median rent. This metric is adjusted for inflation and provides a standardized way to compare changes in housing cost across distance and time. For context, median inflation-adjusted rent in Raleigh increased from $851 per month average in 2008-2012 to $1,145 per month average in 2018-2022, which is approximately a 35% increase (U.S. Census Bureau, 2012; U.S. Census Bureau, 2022). The histogram in Figure 3 reveals a positively skewed distribution, with some neighborhoods experiencing rent increases beyond the average.

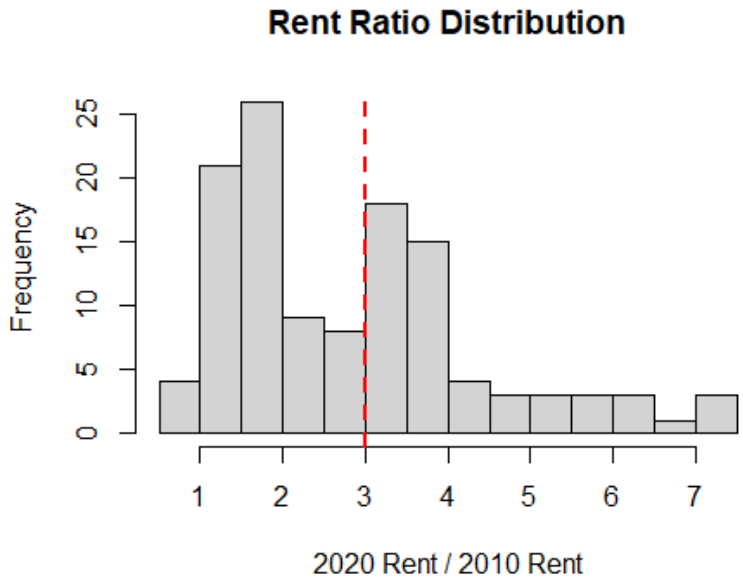

Figure 3. Raleigh Rent Ratio Distribution: A vertical reference line at a rent ratio of three flags areas where rents had tripled over the decade, indicating potential extreme affordability pressures.

To investigate how demographic characteristics related to rent levels, two linear regression models were developed: one for 2010 median rent and one for 2020 median rent. Predictor variables included total population, percent Black and White residents, percent of adults with a bachelor's degree or higher, and median family income. The results, shown in Figure 4, show distinct shifts over time.

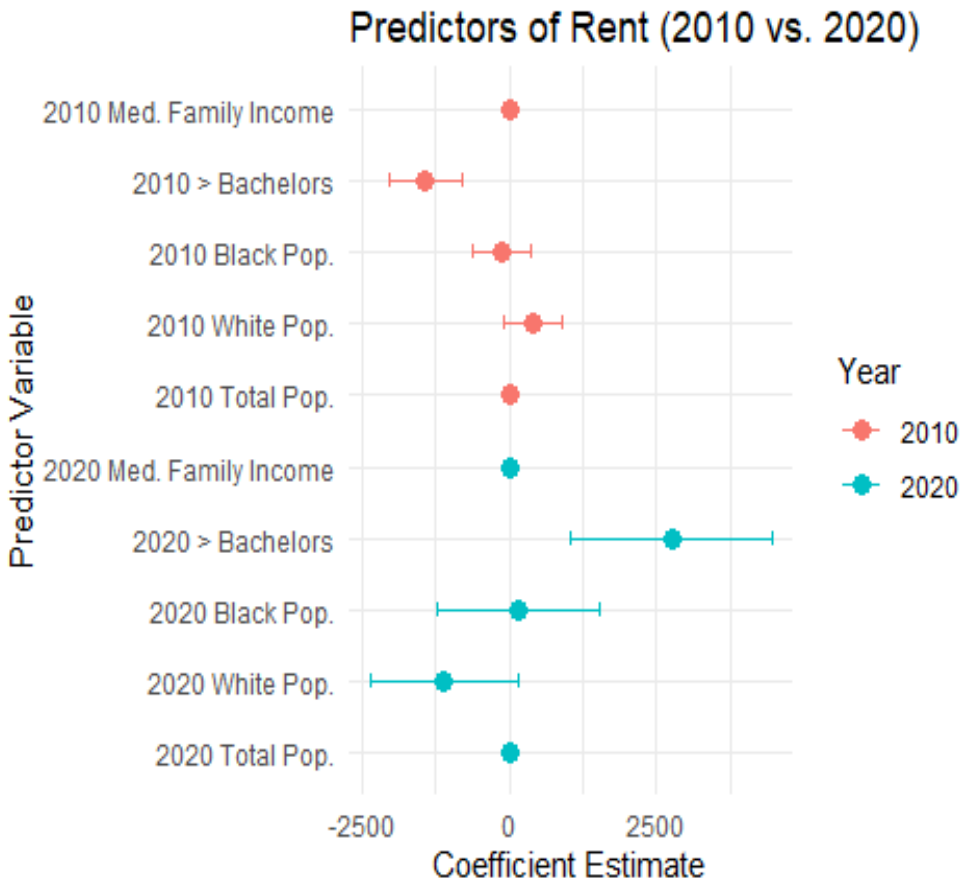

Figure 4. Visualization of linear regression models for 2010 and 2020 median rent using demographic indicators as predictor variables.

Across both models, total population and median family income had coefficient estimates of zero and were not statistically significant predictors of rent, indicating that these variables did not exhibit a measurable influence on rent for either year. A key shift can be seen in educational attainment; while in 2019 a higher share of college educated residents was negatively associated with rent, by 2020 this association transitions and became a significant positive predictor. This could suggest growing rental demand in areas with more highly educated populations, consistent with gentrification patterns (Mohai and Saha 2006; Pearsall, 2010; Beccera, 2022).

Racial composition variables were not statistically significant in either year, though the percentage of White residents in 2020 showed a negative relationship to rent, which may hint at changing neighborhood dynamics (Pinderhughes, 1996; Eckerd and Keeler, 2012). Overall, the results of this analysis highlight a strengthening link between rent levels and socioeconomic advantage over time, particularly in education and income, which are key signals of neighborhood change.

Displacement Pressures

The final analysis assesses potential displacement pressures near brownfields sites, specifically for census block groups where housing values increased by more than 20% above the 2010 baseline, adjusted for inflation. This flag was used to identify geographies where owner occupied housing costs may have outpaced household resources, placing financial strain on residents and signaling potential displacement dynamics. As with previous analyses, key socioeconomic indicators were aggregated by buffer distance from the sites that fell within the selected parameter.

The 0.5 mile-buffer zones consistently exhibited patterns associated with gentrification and heightened displacement risk across all indicators (Figure 5). Mean family income was highest at this distance, suggesting that neighborhoods farther from the sites are attracting and/or retaining more affluent residents. Similarly, the percentage of adults with a bachelor's degree or higher was also greatest in 0.5-mile buffers. These findings suggest an expanding area of influence where housing market appreciation is not confined to the immediate surroundings of brownfields sites.

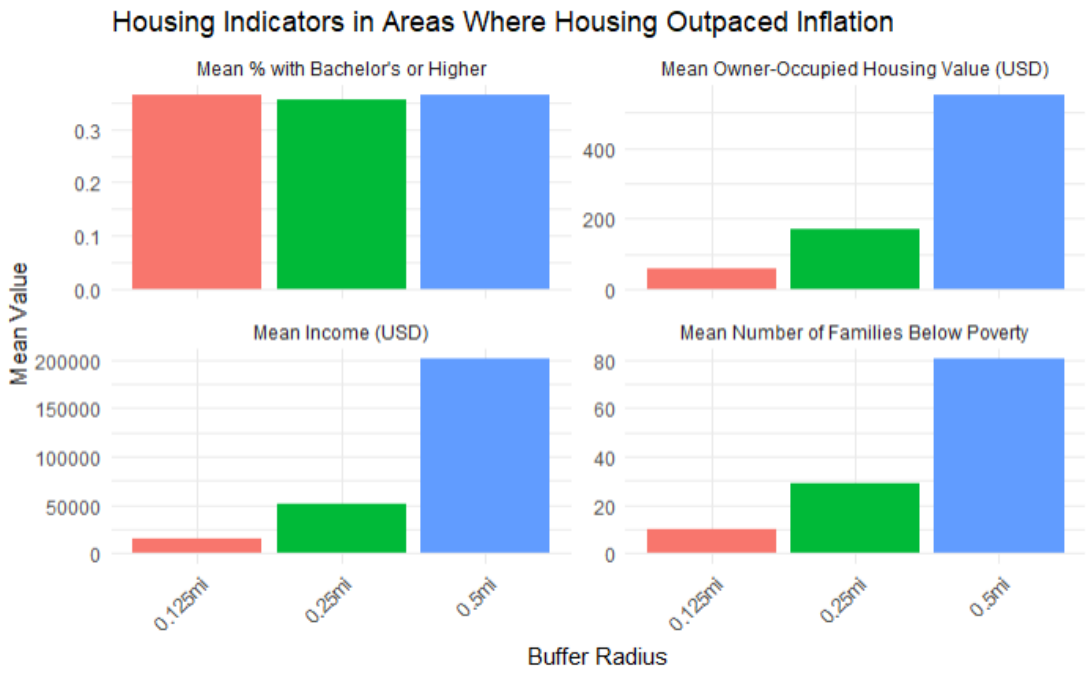

Figure 5. Displacement pressures within neighborhoods in 2020 that had housing values increase by over 20% when compared to corresponding 2010 housing values

Notably, the mean number of families below poverty level was lowest in areas closest to the brownfields site at a buffer distance of 0.125 mile and increasing with distance. This inverse pattern may reflect early-stage displacement, where lower-income households are being pushed out from the most desirable or rapidly changing zones, or alternatively, may indicate barriers to entry in high-cost areas that now exceed affordability thresholds for these populations (Pearsall, 2010; O'Leary et al 2023). These patterns are reinforced by the average value of owner-occupied homes, which is also seen to be highest at 0.5-mile buffer radius. Cumulatively these trends potentially suggest that rising housing values are contributing to exclusionary pressures, even in peripheral zones, extending the spatial footprint of displacement risks beyond the immediate development corridors.

CHAPTER 4. CONCLUSIONS

Overall, the findings from this analysis reveal that Raleigh's landscape has changed significantly over the previous decade. This analysis of brownfields redevelopment and environmental gentrification reveals nuanced interactions between land reuse policies, urban market forces, and social equity. Drawing from spatial and statistical analyses of 42 recorded brownfields sites between 2010 and 2020, the study highlights measurable changes in neighborhood demographics, housing affordability, and socioeconomic composition within proximity to redeveloped sites.

The findings suggest that while brownfields redevelopment has the potential to address environmental injustices by improving public health, stimulating economic revitalization, and repurposing neglected land, it can also intensify existing social inequalities. Notably, nearly half of the census block groups within a 0.5-mile radius of redeveloped sites experienced rent tripling over the study period, indicating mounting housing pressure. Simultaneously, block groups closer to brownfields sites had significantly lower income-to-housing ratios, reflecting growing affordability gaps and heightened displacement vulnerability for lower-income residents.

Educational attainment emerged as a statistically significant predictor of rising rents in 2020, signaling the inflow of more socioeconomically advantaged populations. In contrast, racial composition variables were less predictive, though trends suggest potential demographic shifts consistent with gentrification. The findings also uncovered that displacement risks, measured by

housing value growth outpacing inflation, are not confined to immediate brownfields vicinities, but radiate outward, influencing broader neighborhood dynamics.

Despite the positive fiscal impacts for local governments, such as increased tax revenues and private reinvestment, the social costs of redevelopment may largely fall on historically marginalized populations (Eckerd and Keeler, 2012). This case study of Raleigh illustrates how redevelopment can trigger redevelopment processes that disproportionately benefit newcomers while displacing long-term communities. In conclusion, while brownfields revitalization in Raleigh contributes to environmental remediation and economic development, it should be thoughtfully aligned with community protection mechanisms (Beccera, 2022). Policy tools such as affordable housing preservation and inclusive planning are essential to ensure that those most burdened by environmental legacies can equitably share in the benefits of urban renewal.

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APPENDICES

Appendix A

==========

==========

Thesis: An Analysis of Brownfields Redevelopment and Environmental Gentrification Patterns in Raleigh, North Carolina

Author: Aditi Chakravarty

Date: 6.19.2025

Description:

Loads and analyzes demographic + housing data by buffer distance around brownfields.

Includes optional deeper statistical exploration.

==========

==========

```
#install.packages("janitor")
#install.packages("ggplot2")
#install.packages("broom")
#install.packages("kableExtra")
#install.packages("readxl")

library(readxl)

## Warning: package 'readxl' was built under R version 4.3.3

library (dplyr)

##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag
```

```
## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union

library(janitor)

## Warning: package 'janitor' was built under R version 4.3.3

##
## Attaching package: 'janitor'

## The following objects are masked from 'package:stats':
##
##     chisq.test, fisher.test

library(ggplot2)
library(broom)

## Warning: package 'broom' was built under R version 4.3.3

library(knitr)
library(kableExtra)

## Warning: package 'kableExtra' was built under R version 4.3.3

##
## Attaching package: 'kableExtra'

## The following object is masked from 'package:dplyr':
##
##     group_rows

library(tidyr)

## Warning: package 'tidyr' was built under R version 4.3.3

library(data.table)

## Warning: package 'data.table' was built under R version 4.3.3

##
## Attaching package: 'data.table'

## The following objects are masked from 'package:dplyr':
##
##     between, first, last

library(bit64)

## Loading required package: bit

##
## Attaching package: 'bit'
```

```
## The following object is masked from 'package:data.table':
##
##     setattr

## The following object is masked from 'package:dplyr':
##
##     symdiff

## The following object is masked from 'package:base':
##
##     xor

## Attaching package bit64

## package:bit64 (c) 2011-2017 Jens Oehlschlaegel

## creators: integer64 runif64 seq :

## coercion: as.integer64 as.vector as.logical as.integer as.double as.charac
ter as.bitstring

## logical operator: ! & | xor != == < <= >= >

## arithmetic operator: + - * / %/% %% ^

## math: sign abs sqrt log log2 log10

## math: floor ceiling trunc round

## querying: is.integer64 is.vector [is.atomic} [length] format print str

## values: is.na is.nan is.finite is.infinite

## aggregation: any all min max range sum prod

## cumulation: diff cummin cummax cumsum cumprod

## access: length<- [ [<- [[ [[<-

## combine: c rep cbind rbind as.data.frame

## WARNING don't use as subscripts

## WARNING semantics differ from integer

## for more help type ?bit64

##
## Attaching package: 'bit64'

## The following object is masked from 'package:utils':
##
##     hashtab
```

```
## The following objects are masked from 'package:base':
##
##     %in%, :, is.double, match, order, rank

#set working library
setwd("C:/Users/aditi/OneDrive/Documents/Masters Thesis/R Analysis")

getwd()

## [1] "C:/Users/aditi/OneDrive/Documents/Masters Thesis/R Analysis"

data <- read_excel("BF_Renamed.xlsx")

## New names:
## • `2010 owner-occupied housing units` -> `2010 owner-occupied housing
##   units...25`
## • `2020 owner-occupied housing units` -> `2020 owner-occupied housing
##   units...26`
## • `2010 owner-occupied housing units` -> `2010 owner-occupied housing
##   units...35`
## • `2020 owner-occupied housing units` -> `2020 owner-occupied housing
##   units...36`

data <- data[-c(42,43),]

View(data)

data <- data %>%
  rename(
    Total.Pop10 = `2010 total population`,
    Total.Pop20 = `2020 total population`,
    Pop.Dens10 = `2010 population density per sq. mile`,
    Pop.Dens20 = `2020 population density per sq. mile`,
    Total.Pop10_0_17  = `2010 aggregate (total population 0-17 years)`,
    Total.Pop20_0_17 = `2020 aggregate (total population 0 -17 years)`,
    Total.Pop10_18_64 = `2010 aggregate (total population 18 - 64 years)`,
    Total.Pop20_18_64 = `2020 aggregate (total population 18-64 years)`,
    Total.Pop10_65plus = `2010 aggregate (total population (65+ years)`,
    Total.Pop20_65plus = `2020 aggregate (total population (65+ years)`,
    White.Pop10 = `2010 total population: white alone`,
    White.Pop20 = `2020 total population: white alone`,
    Black.Pop10 = `2010 total population: black or african american alone`,
    Black.Pop20 = `2020 total population: black or african american alone`,
    Asian.Pop10 = `2010 total population: asian alone`,
    Asian.Pop20 = `2020 total population: asian alone`,
    Housing.Units10 = `2010 housing units`,
    Housing.Units20 = `2020 housing units`,
    Owner.Occupied10 = `2010 owner-occupied housing units...25`,
    Owner.Occupied20 = `2020 owner-occupied housing units...26`,
    Vacant.Units10 = `2010 housing units: vacant`,
    Vacant.Units20 = `2020 housing units: vacant`,
```

```
    Vacant.For.Rent10 = `2010 vacant housing units: for rent`,
    Vacant.For.Rent20 = `2020 vacant housing units: for rent`,
    Vacant.For.Sale10 = `2010 vacant housing units: for sale only`,
    Vacant.For.Sale20 = `2020 vacant housing units: for sale only`,
    Occupied.Units10 = `2010 housing units: occupied`,
    Occupied.Units20 = `2020 housing units: occupied`,
    HU.Value10_0_149K = `2010 aggregate (owner occupied hu house value $0-$14
9,999)`,
    HU.Value20_0_149K = `2020 aggregate (owner occupied hu house value $0-$14
9,000)`,
    HU.Value10_150_299K = `2010 owner-occupied hu (house value $150,000 to $2
99,999)`,
    HU.Value20_150_299K = `2020 owner-occupied hu (house value $150,000 to $2
99,000)`,
    HU.Value10_300_499K = `2010 owner occupied hu (house value $300,000 to $4
99,999)`,
    HU.Value20_300_499K = `2020 owner-occupied hu (house value $300,000 to $4
99,000)`,
    HU.Value10_500_749K = `2010 owner occupied hu (house value $500,000 to $7
49,999)`,
    HU.Value20_500_749K = `2020 owner occupied hu (house value $500,000 to $7
49,999)`,
    HU.Value10_750_999K = `2010 owner-occupied hu (house value $750,000 to $9
99,000)`,
    HU.Value20_750_999K = `2020 owner-occupied hu (house value $750,000 to $9
99,000)`,
    HU.Value10_1M_Plus = `2010 owner occupied hu (house value $1,000,000 or m
ore)`,
    HU.Value20_1M_Plus = `2020 owner-occupied hu (house value $1,000,000 or m
ore)`,
    Total.Pop10_25Plus = `2010 population 25 years and over`,
    Total.Pop20_25Plus = `2020 population 25 years and over`,
    Pop10.ED.HS_Less = `2010 population 25 years and over less than high scho
ol ed`,
    Pop20.ED.HS_Less = `2020 population 25 years and over: less than high sch
ool ed`,
    Pop10.ED.HS_Grad = `2010 population 25 years and over: high school gradua
te or equivalent`,
    Pop20.ED.HS_Grad = `2020 population 25 years and over: high school gradua
te or equivalent`,
    Pop10.ED.Bach = `2010 population 25 years and over: bachelor's degree`,
    Pop20.ED.Bach = `2020 population 25 years and over: bachelor's degree`,
    Pop10.ED.Bach_More = `2010 aggregate (more than bachelor's degree)`,
    Pop20.ED_Bach_More = `2020 aggregate (more than bachelor's degree)`,
    Median.Fam.Income10 = `2010 median family income (in 2012 inflation adjus
ted dollars)`,
    Median.Fam.Income20 = `2020 median family income (2022 inflation adjusted
dollars)`,
    Median.Rent10 = `2010 median gross rent`,
    Median.Rent20 = `2020 median gross rent`,
```

```
    Total.Pov10.Families = `2010 Families in Poverty`,
    Total.Pov20.Families = `2020 Families in Poverty`,
    Above.Pov10.Families = `families: income in 2012 at or above poverty leve
l`,
    Above.Pov20.Families = `families: income in 2022 at or above poverty leve
l`,
    Below.Pov10.Families = `families: income in 2012 below poverty level`,
    Below.Pov20.Families = `families: income 2022 below poverty level`,

  )
# Create a data dictionary (ACS can be manually input into description )

names(data)

##  [1] "Buffer Distance mi"
##  [2] "objectid"
##  [3] "bf_name"
##  [4] "address"
##  [5] "city"
##  [6] "bf_acreage"
##  [7] "Total.Pop10"
##  [8] "Total.Pop20"
##  [9] "Pop.Dens10"
## [10] "Pop.Dens20"
## [11] "Total.Pop10_0_17"
## [12] "Total.Pop20_0_17"
## [13] "Total.Pop10_18_64"
## [14] "Total.Pop20_18_64"
## [15] "Total.Pop10_65plus"
## [16] "Total.Pop20_65plus"
## [17] "White.Pop10"
## [18] "White.Pop20"
## [19] "Black.Pop10"
## [20] "Black.Pop20"
## [21] "Asian.Pop10"
## [22] "Asian.Pop20"
## [23] "Housing.Units10"
## [24] "Housing.Units20"
## [25] "Owner.Occupied10"
## [26] "Owner.Occupied20"
## [27] "Vacant.Units10"
## [28] "Vacant.Units20"
## [29] "Vacant.For.Rent10"
## [30] "Vacant.For.Rent20"
## [31] "Vacant.For.Sale10"
## [32] "Vacant.For.Sale20"
## [33] "Occupied.Units10"
## [34] "Occupied.Units20"
## [35] "2010 owner-occupied housing units...35"
```

```
## [36] "2020 owner-occupied housing units...36"
## [37] "HU.Value10_0_149K"
## [38] "HU.Value20_0_149K"
## [39] "HU.Value10_150_299K"
## [40] "HU.Value20_150_299K"
## [41] "HU.Value10_300_499K"
## [42] "HU.Value20_300_499K"
## [43] "HU.Value10_500_749K"
## [44] "HU.Value20_500_749K"
## [45] "HU.Value10_750_999K"
## [46] "HU.Value20_750_999K"
## [47] "HU.Value10_1M_Plus"
## [48] "HU.Value20_1M_Plus"
## [49] "Total.Pop10_25Plus"
## [50] "Total.Pop20_25Plus"
## [51] "Pop10.ED.HS_Less"
## [52] "Pop20.ED.HS_Less"
## [53] "Pop10.ED.HS_Grad"
## [54] "Pop20.ED.HS_Grad"
## [55] "Pop10.ED.Bach"
## [56] "Pop20.ED.Bach"
## [57] "Pop10.ED.Bach_More"
## [58] "Pop20.ED_Bach_More"
## [59] "Median.Fam.Income10"
## [60] "Median.Fam.Income20"
## [61] "Median.Rent10"
## [62] "Median.Rent20"
## [63] "Total.Pov10.Families"
## [64] "Total.Pov20.Families"
## [65] "Above.Pov10.Families"
## [66] "Above.Pov20.Families"
## [67] "Below.Pov10.Families"
## [68] "Below.Pov20.Families"
## [69] "buffer_radius"
```

```
data_dictionary <- data.frame(
  variable_name = names(data),
  type = sapply(data, class),
  description = "",
  units = ""
)

View(data_dictionary)
```

========== Part 2: Analysis ==========

Analysis Questions:

Indicators of interest are pulled from socioeconomic, housing, and demographic ACS data.

1. Where rental values have tripled, what population shifts do we see? What demographic changes

do we see related to race, age, educational attainment, and family poverty?

Triple = B0 + B1*Pop* + *B2*Pop_Black + B3*Pop_White* + *B4*HousingUnits + B5*Vacant

2. Where rental values have not significantly changed, how do the same demographic indicators

compare? What is the relationship between rental values and demographic values?

Create a regression code

Here's where rent is astronomical - what does that mean? Create regression values for this question.

Compare rental values from 2010 to 2010 indicators to 2020 rental values to 2020 indicators.

Which rental values were significant predictors for 2010 and 2020 values. Construct regression curve for both of these values.

3. Have housing values outpaced the national average, when adjusted for inflation? For housing values that have outpaced inflation, do we see increased indicators of displacement in the form an increasing gap between housing value and household incomes? Are there more households with higher educational attainment and incomes?

```
# ----------------------Standardize Data Based on Weighted Average----------
--------------------

# Demographics by Total Population - Age & Ethnicity

data <- data %>%
  mutate(
   data <- data %>%
  mutate(
    pct_black_10 = Black.Pop10 / Total.Pop10,
    pct_black_20 = Black.Pop20 / Total.Pop20,

    pct_white_10 = White.Pop10 / Total.Pop10,
    pct_white_20 = White.Pop20 / Total.Pop20,

    pct_asian_10 = Asian.Pop10 / Total.Pop10,
    pct_asian_20 = Asian.Pop20 / Total.Pop20,

    pct_under17_10 = Total.Pop10_0_17 / Total.Pop10,
    pct_under17_20 = Total.Pop20_0_17 / Total.Pop20,

    pct_18to64_10 = Total.Pop10_18_64 / Total.Pop10,
    pct_18to64_20 = Total.Pop20_18_64 / Total.Pop20,

    pct_65plus_10 = Total.Pop10_65plus / Total.Pop10,
    pct_65plus_20 = Total.Pop20_65plus / Total.Pop20,
  )

  )

# Demographics by Total Population 25 Years and Older - Education

data <- data %>%
  mutate(
    pct_ed_hs_less_10 = Pop10.ED.HS_Less / Total.Pop10_25Plus,
    pct_ed_hs_less_20 = Pop20.ED.HS_Less / Total.Pop20_25Plus,
```

```
    pct_ed_hs_grad_10 = Pop10.ED.HS_Grad / Total.Pop10_25Plus,
    pct_ed_hs_grad_20 = Pop20.ED.HS_Grad / Total.Pop20_25Plus,

    pct_ed_bach_10 = Pop10.ED.Bach / Total.Pop10_25Plus,
    pct_ed_bach_20 = Pop20.ED.Bach / Total.Pop20_25Plus,

    pct_ed_bach_more_10 = Pop10.ED.Bach_More / Total.Pop10_25Plus,
    pct_ed_bach_more_20 = Pop20.ED_Bach_More / Total.Pop20_25Plus,
  )



#Housing by Total Housing Units - Vacancy & Occupancy

data <- data %>%
  mutate(
    pct_vacant_10 = Vacant.Units10 / Housing.Units10,
    pct_vacant_20 = Vacant.Units20 / Housing.Units20,

    pct_occupied_10 = Occupied.Units10 / Housing.Units10,
    pct_occupied_20 = Occupied.Units20 / Housing.Units20,

    pct_owner_occupied_10 = Owner.Occupied10/ Housing.Units10,
    pct_owner_occupied_20 = Owner.Occupied20/ Housing.Units20,

    pct_vacant_for_rent_10 = Vacant.For.Rent10 / Housing.Units10,
    pct_vacant_for_rent_20 = Vacant.For.Rent20 / Housing.Units20,

    pct_vacant_for_sale_10 = Vacant.For.Sale10 / Housing.Units10,
    pct_vacant_for_sale_20 = Vacant.For.Sale20 / Housing.Units20
  )


data <- data %>%
  mutate(
    pct_families_at_or_above_poverty_10 = Above.Pov10.Families / Total.Pov10.
Families,
    pct_families_at_above_poverty_20 = Above.Pov20.Families / Total.Pov20.Fam
ilies,

    pct_families_below_poverty_10 = Below.Pov10.Families / Total.Pov10.Famili
es,
    pct_families_below_poverty_20 = Below.Pov20.Families / Total.Pov20.Famili
es
  )


View(data)
```

```r
# --------------- 0. Calculate necessary variables for analysis ------------
--
# Create flags for conditions of interest (adjust as necessary):
# - rent_tripled: Rent in 2020 at least 3x higher than 2010
# - rent_astronomical: Among top 5% of 2020 rents
# - housing_outpaced: Housing values rose faster than national inflation (~20
%)
# - income_to_housing_ratio: Rough measure of affordability

data <- data %>%
  mutate(
    rent_ratio = Median.Rent20 / Median.Rent10,
    rent_tripled = rent_ratio >= 3,
    rent_astronomical = Median.Rent20 >= quantile(Median.Rent20, 0.95, na.rm
= TRUE),
    inflation_factor = 1.2,
    housing_outpaced = pct_owner_occupied_20 > pct_owner_occupied_10 * inflat
ion_factor,
    income_to_housing_ratio = Median.Fam.Income20 /
      pct_owner_occupied_20
  )

library(dplyr)

buffer_summary <- data %>%
  group_by(buffer_radius) %>%
  summarize(
    n = n(),
    percent_rent_tripled = mean(rent_tripled, na.rm = TRUE) * 100,
    percent_rent_astronomical = mean(rent_astronomical, na.rm = TRUE) * 100,
    percent_housing_outpaced = mean(housing_outpaced, na.rm = TRUE) * 100,
    avg_income_to_housing_ratio = mean(income_to_housing_ratio, na.rm = TRUE)
  ) %>%
  arrange(desc(percent_rent_tripled))  # Sort by variable of interest

View(buffer_summary)

# --------------- 1. Rent and Demographics ---------------
# 1.1 Summary of demographics in areas where rent tripled
data %>%
  filter(rent_tripled) %>%        # STEP 1: Subset to sites where rent_triple
d == TRUE
  group_by(buffer_radius) %>%     # STEP 2: Break results out by distance ban
d (0.125, 0.25, 0.5mi)
  summarise(
    mean_pop_change = mean(Total.Pop20 - Total.Pop10, na.rm = TRUE),
    mean_black = mean(pct_black_20, na.rm = TRUE),
    mean_white = mean(pct_white_20, na.rm = TRUE),
    mean_edu = mean(pct_ed_bach_more_20, na.rm = TRUE),
```

```
    mean_poverty = mean(pct_families_below_poverty_20, na.rm = TRUE)
  )
```

```
## # A tibble: 3 × 6
##   buffer_radius mean_pop_change mean_black mean_white mean_edu mean_povert
y
##   <chr>                   <dbl>      <dbl>      <dbl>    <dbl>        <dbl
>
## 1 0.125mi                  250.      0.172      0.679    0.259      0.0104
## 2 0.25mi                   695.      0.160      0.694    0.255      0.0086
2
## 3 0.5mi                   1728.      0.196      0.664    0.252      0.0232
```

```
# 1.2 Extended demographics analysis
data %>%
  filter(rent_tripled) %>%
  group_by(buffer_radius) %>%
  summarise(
    mean_pop_change = mean(Total.Pop20 - Total.Pop10, na.rm = TRUE),

    # Racial change
    black_change = mean(pct_black_20 - pct_black_10, na.rm = TRUE),
    white_change = mean(pct_white_20 - pct_white_10, na.rm = TRUE),

    # Age group shifts
    youth_change = mean(pct_under17_20 - pct_under17_10, na.rm = TRUE),
    senior_change = mean(pct_65plus_20 - pct_65plus_10, na.rm = TRUE),

    # Income & affordability
    mean_income = mean(Median.Fam.Income20, na.rm = TRUE),
    rent_burden_ratio = mean(Median.Rent20 / Median.Fam.Income20, na.rm = TRU
E),

    # Housing market change
    vacant_2020 = mean(pct_vacant_20, na.rm = TRUE),
    occupied_2020 = mean(pct_occupied_20, na.rm = TRUE)
  )
```

```
## # A tibble: 3 × 10
##   buffer_radius mean_pop_change black_change white_change youth_change
##   <chr>                   <dbl>        <dbl>        <dbl>        <dbl>
## 1 0.125mi                  250.       -0.186       0.102       -0.0407
## 2 0.25mi                   695.       -0.185       0.0998      -0.0408
## 3 0.5mi                   1728.       -0.178       0.0953      -0.0372
## # ℹ 5 more variables: senior_change <dbl>, mean_income <dbl>,
## #   rent_burden_ratio <dbl>, vacant_2020 <dbl>, occupied_2020 <dbl>
```

```
#--------------- 2. Significant Rent Change and Demographics ---------------

  # 2.1 Compare Areas Where Rent Didn't significantly change
  # 2.1.1 Get an idea of how much has changed by plotting ratio
```

```r
#DISCUSS - is there a better way to visualize this? Is looking at rent ratio helpful/does it make sense?
summary(data$rent_ratio)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.5034  1.5346  2.5597  2.8337  3.5709  7.4419
```

```r
hist(data$rent_ratio, breaks = 20, main = "Rent Ratio Distribution", xlab = "2020 Rent / 2010 Rent")

abline(v = 3, col = "red", lwd = 2, lty = 2)
```


```r
# 2.1.2 Pick what "significant" change means, start with bottom 20 % ? - discuss w/ Jen
data <- data %>%
  mutate(rent_low_increase = rent_ratio <= quantile(rent_ratio, 0.2, na.rm = TRUE))

data  %>%
  filter(rent_low_increase) %>%
  group_by(buffer_radius) %>%
  summarise(
    mean_pop = mean(Total.Pop20, na.rm = TRUE),
    mean_black = mean(pct_black_20, na.rm = TRUE),
    mean_white = mean(pct_white_20, na.rm = TRUE),
    mean_income = mean(Median.Fam.Income20, na.rm = TRUE),
```

```
    mean_edu = mean(pct_ed_bach_more_20, na.rm = TRUE),
    mean_poverty = mean(pct_families_below_poverty_20, na.rm = TRUE)
  )
```

```
## # A tibble: 3 × 7
##   buffer_radius mean_pop mean_black mean_white mean_income mean_edu mean_p
overty
##   <chr>            <dbl>      <dbl>      <dbl>       <dbl>    <dbl>
<dbl>
## 1 0.125mi           494.      0.166      0.691      24381.    0.232
0.132
## 2 0.25mi           1307.      0.181      0.668      64729.    0.248
0.116
## 3 0.5mi            4360.      0.176      0.658     218480.    0.255
0.108
```

```
# 2.2 Run Regressions for 2010 vs. 2020 Rent Predictors
# 2.2.1 2010 rent model
model_2010 <- lm(Median.Rent10 ~
                   Total.Pop10 +
                   pct_black_10 +
                   pct_white_10 +
                   pct_ed_bach_10 +
                   Median.Fam.Income10,
                 data = data)

# 2.2.2 2020 rent model
model_2020 <- lm(Median.Rent20 ~
                   Total.Pop20 +
                   pct_black_20 +
                   pct_white_20 +
                   pct_ed_bach_20 +
                   Median.Fam.Income20,
                 data = data)


# Print summaries
summary(model_2010)
```

```
##
## Call:
## lm(formula = Median.Rent10 ~ Total.Pop10 + pct_black_10 + pct_white_10 +
##     pct_ed_bach_10 + Median.Fam.Income10, data = data)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -687.78  -82.67  -37.48   46.03  961.71
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
```

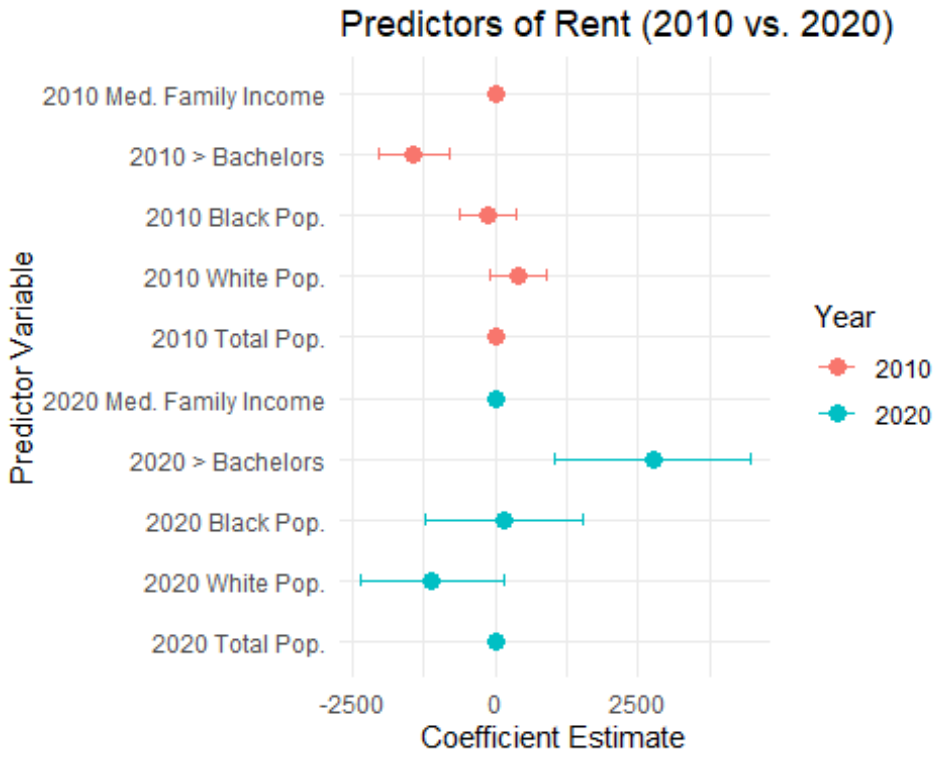
```
## (Intercept)          2.482e+02  2.356e+02   1.054    0.294
## Total.Pop10          2.677e-01  2.522e-02  10.616  < 2e-16 ***
## pct_black_10        -1.213e+02  2.516e+02  -0.482    0.631
## pct_white_10         3.972e+02  2.547e+02   1.559    0.122
## pct_ed_bach_10      -1.420e+03  3.103e+02  -4.575 1.21e-05 ***
## Median.Fam.Income10  3.629e-03  5.022e-04   7.226 5.84e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 185.7 on 115 degrees of freedom
## Multiple R-squared:  0.9436, Adjusted R-squared:  0.9411
## F-statistic: 384.8 on 5 and 115 DF,  p-value: < 2.2e-16
```

```
summary(model_2020)
```

```
##
## Call:
## lm(formula = Median.Rent20 ~ Total.Pop20 + pct_black_20 + pct_white_20 +
##     pct_ed_bach_20 + Median.Fam.Income20, data = data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1808.48  -188.63    41.92   176.66  1751.53
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)         -3.714e+02  4.509e+02  -0.824   0.4118
## Total.Pop20          4.016e-01  4.336e-02   9.261 1.37e-15 ***
## pct_black_20         1.577e+02  7.013e+02   0.225   0.8225
## pct_white_20        -1.103e+03  6.338e+02  -1.741   0.0844 .
## pct_ed_bach_20       2.754e+03  8.617e+02   3.196   0.0018 **
## Median.Fam.Income20  7.999e-03  5.645e-04  14.171  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 472.5 on 115 degrees of freedom
## Multiple R-squared:  0.9566, Adjusted R-squared:  0.9547
## F-statistic: 507.3 on 5 and 115 DF,  p-value: < 2.2e-16
```

```
# Combine and label year
tidy_2010 <- tidy(model_2010, conf.int = TRUE) %>% mutate(year = "2010")
tidy_2020 <- tidy(model_2020, conf.int = TRUE) %>% mutate(year = "2020")

# Combine models
tidy_combined <- bind_rows(tidy_2020, tidy_2010) %>%  # note: 2020 first
  filter(term != "(Intercept)")

# Order indicators
term_levels <- c(
  "Total.Pop20",
```

```
  "pct_white_20",
  "pct_black_20",
  "pct_ed_bach_20",
  "Median.Fam.Income20",
  "Total.Pop10",
  "pct_white_10",
  "pct_black_10",
  "pct_ed_bach_10",
  "Median.Fam.Income10"
)
# Label indicators for plot

term_labels <- c(
  "Total.Pop20" = "2020 Total Pop.",
  "pct_white_20" = "2020 White Pop.",
  "pct_black_20" = "2020 Black Pop.",
  "pct_ed_bach_20" = "2020 > Bachelors",
  "Median.Fam.Income20" = "2020 Med. Family Income",
  "Total.Pop10" = "2010 Total Pop.",
  "pct_white_10" = "2010 White Pop.",
  "pct_black_10" = "2010 Black Pop.",
  "pct_ed_bach_10" = "2010 > Bachelors",
  "Median.Fam.Income10" = "2010 Med. Family Income"
)


# Set factor levels for ordering
tidy_combined$term <- factor(tidy_combined$term, levels = term_levels)

# Plot
ggplot(tidy_combined, aes(x = estimate, y = term, color = year)) +
  geom_point(position = position_dodge(width = 0.5), size = 3) +
  geom_errorbarh(aes(xmin = conf.low, xmax = conf.high),
                 position = position_dodge(width = 0.5), height = 0.2) +
  scale_y_discrete(labels = term_labels) +
  labs(title = "Predictors of Rent (2010 vs. 2020)",
       x = "Coefficient Estimate",
       y = "Predictor Variable",
       color = "Year") +
  theme_minimal()
```




```
# --------------- 3.Housing ---------------
# 3.1 Create a housing inflation flag and affordability ratio
data <- data %>%
  mutate(
    housing_outpaced = pct_owner_occupied_20 > pct_owner_occupied_10 * 1.2,
# 20% inflation adjustment
    income_to_housing_ratio = Median.Fam.Income20 / Owner.Occupied20
  )

# 3.2 Filter for housing-outpaced areas only
housing_outpaced_data <- data %>%
  filter(housing_outpaced)

# 3.3 Summarize key indicators by buffer
housing_summary <- housing_outpaced_data %>%
  group_by(buffer_radius) %>%
  summarise(
    mean_income = mean(Median.Fam.Income20, na.rm = TRUE),
    mean_edu = mean(pct_ed_bach_20, na.rm = TRUE),
    mean_poverty = mean(Below.Pov20.Families, na.rm = TRUE),
    mean_housing_value = mean(Owner.Occupied20, nr.rm = TRUE),
  )

indicator_labels <- c(
  mean_income = "Mean Income (USD)",
  mean_edu = "Mean % with Bachelor's or Higher",
  mean_poverty = "Mean Number of Families Below Poverty",
```

```
  mean_housing_value = "Mean Owner-Occupied Housing Value (USD)"
)

# 3.4 Pivot longer for visualization
housing_long <- housing_summary %>%
  pivot_longer(
    cols = -buffer_radius,
    names_to = "indicator",
    values_to = "mean_value"
  )

# 3.5 Plot
ggplot(housing_long, aes(x = buffer_radius, y = mean_value, fill = buffer_rad
ius)) +
  geom_col(show.legend = FALSE) +
   facet_wrap(~ indicator, scales = "free_y", labeller = labeller(indicator =
indicator_labels)) +
  labs(
    title = "Housing Indicators in Areas Where Housing Outpaced Inflation",
    x = "Buffer Radius",
    y = "Mean Value"
  ) +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```