Race, Poverty, and the Changing American Suburbs

Michael Neubauer* *(Job market paper)* and Jacob Fabian

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Abstract

We study the relationship between the increase in Black suburbanization and the changing geographic distribution of poverty. We build a model of segregation and income sorting that demonstrates how the departure of wealthy White residents from suburban areas that Black families enter can increase suburban poverty. Empirically, we construct a shift-share instrument for changes in the Black share of Northern suburbs based on population flows from the Great Migration. Our results at the metropolitan-area level indicate that overall and non-black suburban poverty increase as a result of Black suburbanization, thereby disproportionately exposing Black residents to the increase in suburban poverty. We find that wealthier incumbent residents left suburbs that Black residents entered, reducing home prices and inducing lower-income residents to move into the suburbs. Using a new instrument to analyze these mechanisms within metropolitan areas yields similar results. Our findings provide another example of destination responses impeding Black Americans' ability to move to opportunity.

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1 Introduction

The American suburbs are changing. Since 1990, the suburban population has grown by 50%. At the same time, the suburbs have experienced two major demographic trends. First, the Black suburban population has doubled since 1990 in a wave of suburbanization of predominantly middle-income Black families (Bartik and Mast 2023). Second, suburban poverty has increased, as documented by Kneebone and Garr (2010) and Allard (2017), as we calculate that the suburban population under the poverty line has nearly doubled since 1990.

While middle-income Black families moved to the suburbs seeking improved housing conditions and neighborhood amenities (Bartik and Mast 2023), the suburbs are now getting poorer. American history is replete with examples of White families moving away from new Black neighbors, leading to entrenched segregation (Shertzer and Walsh (2019), Rothstein (2017), Boustan (2010)). A similar dynamic could be at play among wealthier suburban residents, leaving middle-income Black families, who moved to the suburbs in pursuit of better neighborhoods, instead finding the suburbs growing poorer around them.

This paper studies the relationship between growing Black suburbanization and increasing suburban poverty. We begin by developing a simple model of residential choice that demonstrates how suburban poverty can increase when richer residents leave suburban neighborhoods that Black families enter. In the model, we assume that residents of a metropolitan area choose where to live based on prices, demographics, and preferences for public goods. The model predicts that in racially integrated equilibria, poorer White residents and richer Black residents will live together. However, the model does not predict how much suburban poverty will change for a given increase in the Black suburban population. We turn to the empirical analysis to estimate this relationship.

Empirically, we estimate the extent to which suburban poverty increased as a result of Black suburbanization. To do so, we use a shift-share instrument for the racial composition of Northern suburbs. Our instrument uses three sources of variation. It combines the growth (shifts, or shocks) in Black out-migration from each Southern county during the Great Migration with pre-existing migrant networks (shares) that linked Southern counties to Northern cities. It also incorporates the distance between Northern suburbs and the primary Black neighborhood in each city. Taken together, these sources of variation predict our treatment, the migration of Black families to the suburbs.

Our instrument relies on exogeneity of the shocks for identification (Borusyak et al. 2022). It satisfies the exclusion restriction if shocks to Black migration from Southern counties between 1940 and 1970 are unrelated to unobserved correlates of trends in Northern suburban poverty from 1990 to 2019[1]. For example, if one worries that Black families chose to move to suburban areas that were already becoming poorer, our instrument addresses this issue so long as shocks to Black out-migration from the South during the Great Migration are not related to these trends in Northern suburban poverty today.

Using this instrument, we find that suburban poverty rises in response to Black suburbanization, leaving Black suburban residents unduly affected by the increase in suburban poverty. The share of the poor metropolitan-area population that lives in the suburbs increases by about two percentage points in response to a one percentage point increase in the Black share of the suburban population. We find that Black suburbanization precipitates an increase in the proportion of poor non-black residents that live in the suburbs as well.

We find that wealthier incumbent residents left suburbs that Black suburbanites entered, reducing home prices and inducing lower-income residents to move into the suburbs. Specifically, using the same instrument for Black suburbanization as above, we find that growth in the suburban Black population decreases the share of wealthy residents living in the suburbs and depresses growth in bottom-quartile home prices. Using Census microdata to analyze the migration of lower-income residents, we find a strong correlation between Black suburbanization and the subsequent movement of lower-income residents into the suburbs.

Additionally, while our analysis indicates that Black suburbanization and suburban poverty are primarily related through sorting, we find that approximately one million incumbent suburban residents entered poverty during this time period. Our back-of-the-envelope calculation indicates that changes in educational attainment can explain at most 7% of this increase. Though we do not quantify its impact, changes in public good provision may also contribute to the increase in the incumbent poor population, as we find that overall property tax collections and school quality decrease in suburbs that are becoming poorer. Since we cannot explain most of the increase in poverty among incumbent suburban residents, this remains an important area for future research.

This paper builds upon three strands of literature. First, we contribute to the literature studying racial change and incumbent flight, such as Card et al. (2008), Boustan (2010), and Shertzer and Walsh (2019). Shertzer and Walsh (2019) and Boustan (2010) document how White residents fled from Black migrants to Northern cities (between 1900 and 1930, and 1940 and 1970, respectively), while Card et al. (2008) describes non-linearities in incumbent responses to racial change from 1970 to 2000. Akbar et al. (2022) documents home price declines when neighborhoods transitioned to majority Black in the 1940s. We build on these papers by studying racial change in present-day American suburbs.

[1] As we explain in Section 4, the suburban poverty variables are converted to the level of the shocks for our regression analysis and formal expression of the exclusion restriction.

Further, while these papers focus on shorter-term demographic turnover among incumbent residents, our paper examines the longer-term population churn that occurred after Black migration. Specifically, though these papers document incumbent flight, they do not address the subsequent in-movement of the poor non-black population, which we track using public Census microdata. We document the longer-term series of events that accompanied Black migration to the suburbs: wealthier incumbent residents left, property prices fell, and poorer residents moved in.

Second, this paper is related to a literature, such as Derenoncourt (2022) and Baran et al. (2024), that finds that the general equilibrium effects from large-scale Black "moves to opportunity" are smaller than the effects of individual moves (such as in Chetty et al. (2016), Chyn (2018), and Chyn et al. (2023)). Derenoncourt (2022) finds that destination reactions to the Great Migration diminish the gains that Black families accrue from moving to Northern cities, while Baran et al. (2024) finds that many Northern destinations offering Black children improved opportunities in the 1940s no longer do so today. Akbar et al. (2022) document how, even during the Great Migration, inflated rental prices and deflated home values diminished the economic gains that migrating Black individuals could enjoy.

We document a similar pattern while studying the subsequent, and currently ongoing, wave of Black migration: to the suburbs. We find that as Black residents suburbanize, wealthier residents leave, neighborhoods change, and Black suburban residents are increasingly exposed to poverty. Neighborhood change in the suburbs may be an important mechanism reducing the gains from moving to the North that Black residents in Great Migration destinations experience. Suburban poverty is therefore another example of how destination reactions have made it harder for Black Americans to "move to opportunity" for at least the better part of a century.

Finally, this paper enriches our understanding of the spatial distribution of income within metropolitan areas. Though we investigate different mechanisms, our empirical evidence supports the theoretical predictions of "the poor mov(ing) to the suburbs" from as early as LeRoy and Sonstelie (1983). More recently, the literature studying gentrification, such as Couture and Handbury (2020) and Couture, Gaubert, et al. (2024), has documented how the spatial distribution of income in urban areas has changed. We do the same for suburban areas, documenting the increase in suburban poverty, showing how poorer non-black individuals moved to the suburbs as a result of Black suburbanization, and discussing how poverty increased among incumbent suburban residents for reasons we cannot fully explain. These papers, considered together with this paper, allow us to better understand how the spatial distribution of income is changing throughout the entire metropolitan area.

2 Black Suburbanization and Suburban Poverty: Data and Description

In this section, we describe the data we need to determine the relationship between Black suburbanization and the changing geography of poverty. We use these data to provide an overview of national trends in Black suburbanization and suburbanization of poverty. We then show that these trends are related to each other: they occur in the suburbs of the same metropolitan areas.

2.1 Black suburbanization

To document the increase in the Black suburban population since 1990, we classify every census tract in the country as urban, suburban, or rural based on a map developed by the National Center for Education Statistics (NCES)[2]. We obtain data on suburban racial composition from the decennial Census (1990) and five-year American Community Survey (ACS, 2015-2019)[3]. We measure the total population and the Black non-Hispanic population in each suburban census tract.

Using this data, we calculate that between the 1990 decennial Census and 2015-2019 ACS, the Black suburban population increased by 8.3 million. Black suburbanization was largely driven by middle-income Black families searching for improved amenities and housing conditions (Bartik and Mast 2023), as the authors show that improved neighborhood amenities and affordable housing prices together account for 90% of observed Black suburbanization. It is these higher-income Black families who were "disproportionately able to suburbanize and take advantage of falling discrimination in the wake of the Fair Housing Act" (Bartik and Mast 2023). Using the 2015-2019 ACS, we show in Appendix Figure A.1 that most Black suburban residents are middle-income. These findings are echoed in Colmer et al. (2024), who use IRS tax data from 2016 to document that the percentage of Black households living in the suburbs increases with income.

Using the 1990 decennial Census and 2015-2019 ACS, we calculate in Appendix Table A.1 that the increase in the poor Black suburban population represents only 17.6% of the total increase in the poor suburban population over this time period. Specifically, the poor

[2] The U.S. government does not officially define suburban areas. The NCES defines the suburbs as all land within Metropolitan Statistical Areas (MSAs) that is not within a principal city of the MSA and is not rural. This definition is similar to that used in Bartik and Mast (2023), though those authors include non-first principal cities (such as Newark, NJ) and rural areas within MSAs as suburbs. We believe those areas should be classified as urban and rural, respectively. We use the NCES's classifications from 2015 to construct the suburban area of every MSA in the country.

[3] We use Social Explorer to obtain this tract-level data with constant 2010-tract boundaries.

suburban population increased from 7.23 to 14.19 million, while the poor Black suburban population increased from 1.32 to 2.55 million.

2.2 Suburban poverty

In this section we describe how, though starting from a low level, suburban poverty has increased concurrently with Black suburbanization. We decompose the increase in poverty into that coming from movers versus from stayers to help elucidate causes of the increase.

2.2.1 Quantifying the increase in suburban poverty

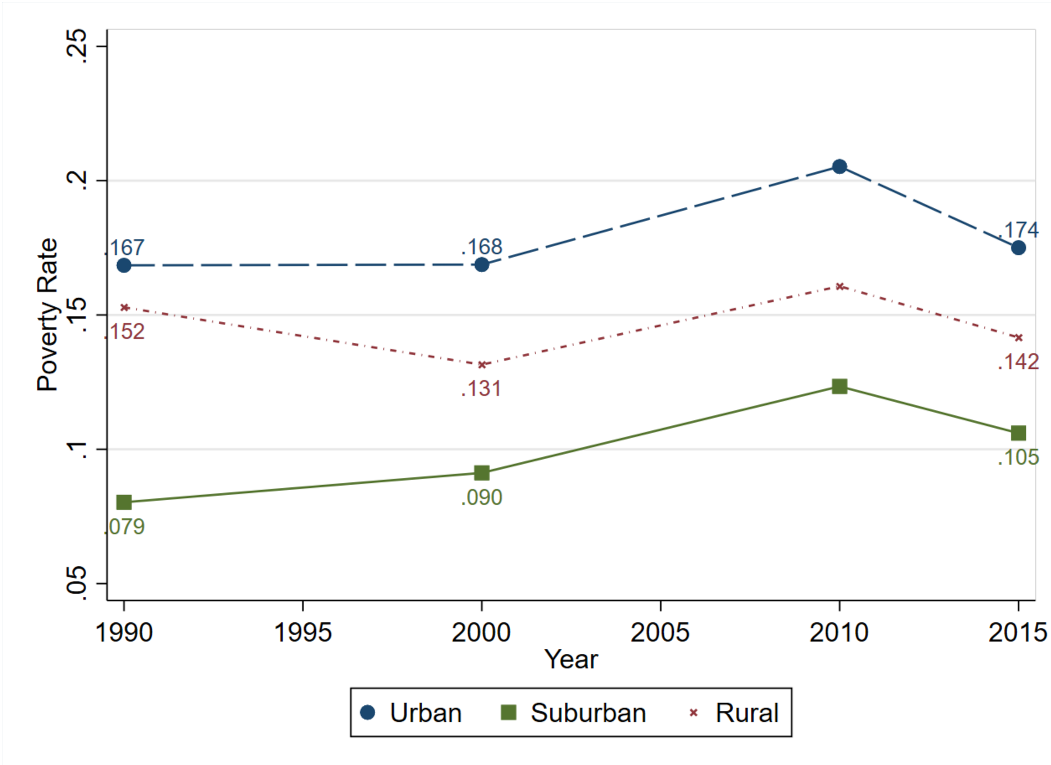
We quantify the increase in suburban poverty in two ways. First, we show that the poverty rate in the suburbs has increased, both absolutely and relative to urban and rural areas. Second, we show that the share of impoverished Americans who live in the suburbs has risen. These broad trends have previously been identified[4], but have not been discussed at length in the economics literature.

We obtain data on poverty within census tracts from the decennial Census (1990) and five-year ACS (2015-2019). A household is in poverty in a given year if its household income is below the federal poverty line for a household of its size in that year. The federal poverty line is set nationally and does not vary by location. We count the number of people who are in households that are in poverty in each census tract.

Analyzing this data, Figure 1 shows that the suburban poverty rate increased by 2.6 percentage points between 1990 and 2015-2019. In contrast, the rural poverty rate declined and the urban poverty rate increased by 0.7 percentage points during this time. The suburban poverty rate increased during the economic expansion of the 1990s, and has decreased relatively slowly since the end of the Great Recession.

[4] For example, see Kneebone and Garr (2010) or Allard (2017).

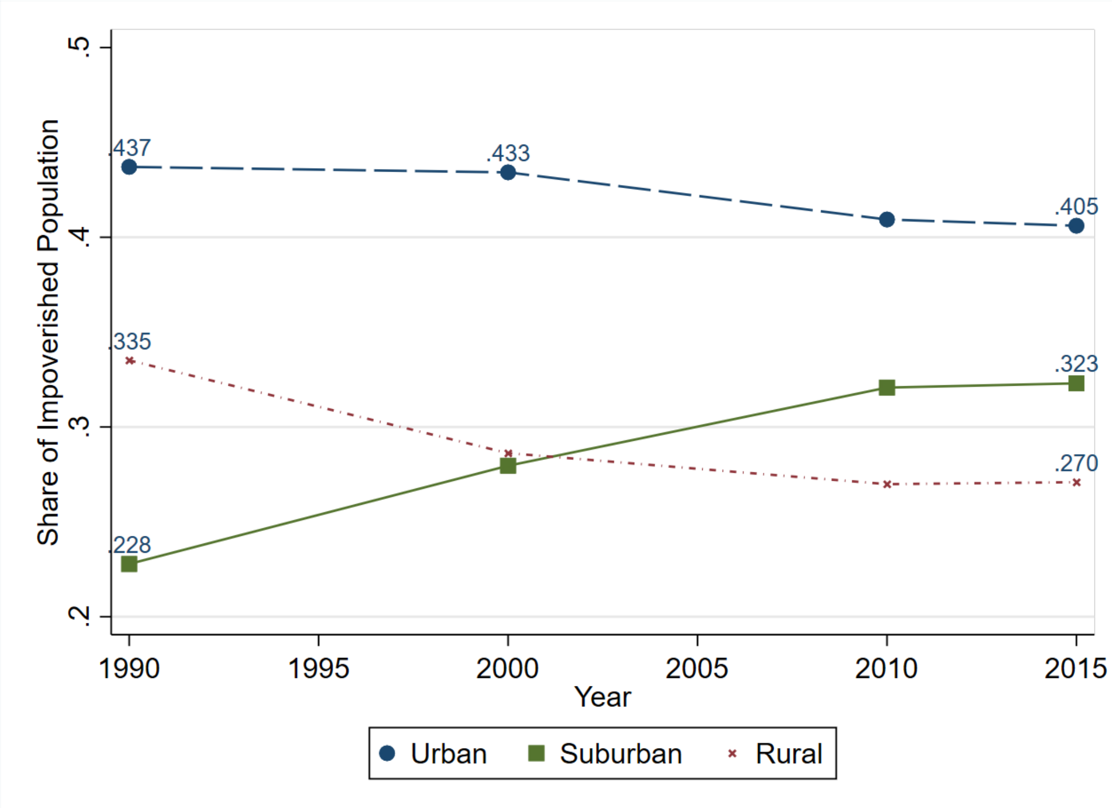
Figure 1: Poverty Rates



Note: Poverty data from decennial Census and five-year ACS tract-level estimates. Urban, suburban, and rural classifications based on data from the National Center for Education Statistics.

The proportion of all impoverished people who live in the suburbs also increased over this period. While our calculations indicate that a plurality of impoverished people live in urban areas, the gap between the number of urban and suburban residents below the poverty line has decreased. As we show in Figure 2, the percentage of impoverished individuals who live in the suburbs has increased by 9.5 percentage points during this time, while the percentage of all Americans who live in the suburbs has only increased by 4.6 percentage points.

Figure 2: Poverty Shares



Note: Poverty data from decennial Census and five-year ACS tract-level estimates. Urban, suburban, and rural classifications based on data from the National Center for Education Statistics.

2.2.2 Decomposing the increase in suburban poverty

Though we know that the suburbs are becoming poorer at the same time that Black residents move in, we want to determine whether the increase in poverty is driven by increasing poverty among incumbent suburban residents or by poor people moving into the suburbs. In this subsection, we decompose the increase in suburban poverty into these two components.

We use publicly available microdata from the decennial Census (1990 and 2000) and one-year ACS files (2005-2019) to conduct this analysis. The microdata's information on previous residence allows us to measure the increase in suburban poverty among migrants (which we refer to as poverty attraction) and incumbent suburban residents (which we refer to as poverty creation). We calculate poverty attraction as the net migration into the suburbs of impoverished individuals[5], and poverty creation as the change in the number of individuals

[5] For consecutive years ($t-1$ and t), such as the years for which we have yearly data (2006-2019), poverty attraction and creation sum to equal the change in the number of suburban poor, as in Equation 17. For the years for which we do not have yearly data (1990, 2000, 2005), this relationship no longer holds because the data for poverty and migration cover different time periods.

under the poverty line between t and $t + 1$ among those who were in the suburbs in year t. More details on our calculations are available in Appendix A.3.3.

We show in Appendix Figure A.2 that the suburbs attracted poverty in every year except 1990, while the suburbs generally created poverty in concert with the business cycle. Between 2008 and 2011 the suburbs created more than half a million poor people every year. After 2011, suburban poverty fell every year except 2013. Nevertheless, our calculations, reflected in more detail in Appendix Table A.2, indicate that the suburbs created poverty even during the period of relatively favorable economic conditions between 1990 and 2005[6]. Overall, we estimate that since 1990, on net the suburbs have created 0.99 million incumbent poor individuals and attracted 1.66 million poor individuals to move in.

2.3 Black Suburbanization and Suburban Poverty

Though both the Black and impoverished suburban populations increased between 1990 and 2015-2019 at the national level, they may have increased in different metropolitan areas. However, we find that suburban poverty increased in the same Metropolitan Statistical Areas (MSAs) that experienced higher levels of Black suburbanization.

To analyze these variables at the MSA level, we calculate changes between the 1990 decennial Census and the 2015-2019 five-year ACS. Our measure of the increase in suburban poverty is the percentage point change in the share of an MSA's poor population that lives in the suburbs. Since the suburban population increased during this time period, we control for the change in the share of the MSA's total population that lives in the suburbs in our regressions. Our results then capture an increase in the poor suburban population that cannot be explained by population growth alone. We measure Black suburbanization as the percentage point change in the share of the suburban population that is Black.

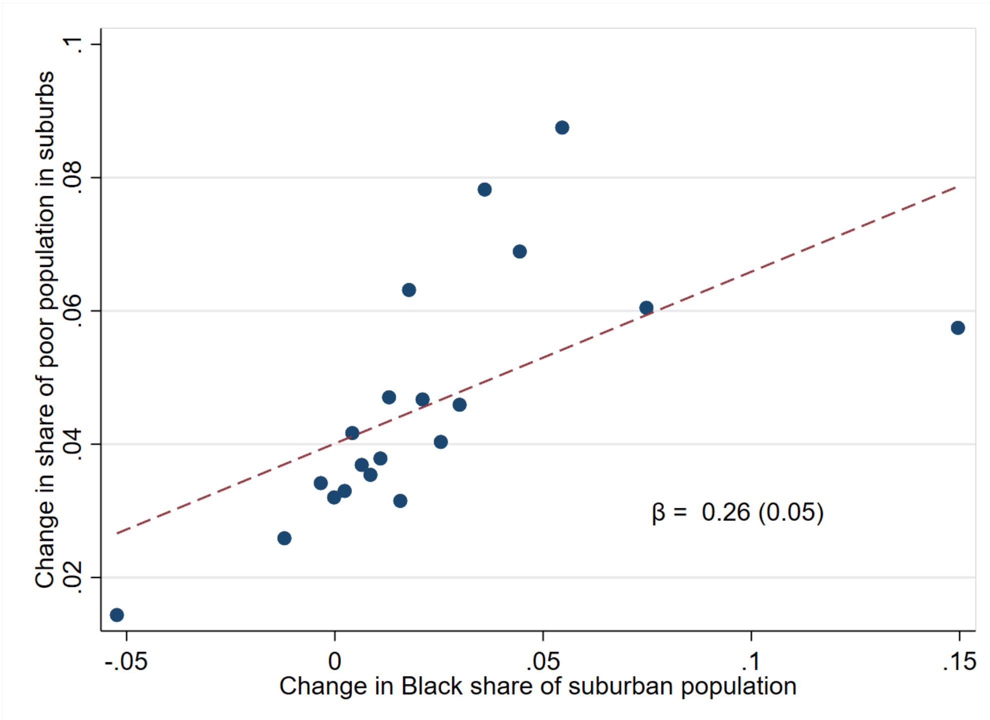
Our summary of these variables in Appendix Table A.3 reveals that between 1990 and 2015-2019 the average share of an MSA's poor population that lives in the suburbs increased by 4.6 percentage points, while the average share of an MSA's total population that lives in the suburbs increased by 3.6 percentage points. On average, the Black share of the suburban population increased by 2.2 percentage points.

To determine the relationship between these variables at the MSA level, we regress our measure of the increase in suburban poverty on the change in the suburban Black share, controlling for the change in the suburban share of the MSA's population. Our results, summarized in Figure 3, demonstrate that Black suburbanization has a statistically significant

[6]Our calculation of the amount of suburban poverty created and attracted for 1990, 2000, and 2005 relies on our assumption that unobserved migration flows (in the earlier part of the decade) are proportional to observed migration flows (in the later part of the decade).

positive correlation with changes in suburban poverty (t=4.9). Suburban areas with larger increases in their Black population became poorer.

Figure 3: Black suburbanization and suburban poverty



Note: MSA-level binscatter of the change in the share of the poor population that lives in the suburbs on the change in the share of the suburban population that is Black, controlling for the change in the share of the MSA population that is suburban. All variables are measured as changes between the 1990 decennial Census and 2015-2019 five-year ACS. There are 383 MSAs represented in the binscatter.

Though the vast majority of Black suburban residents are not poor (Appendix Table A.1), an increase in the suburban Black poor population could mechanically drive this relationship. However, a similar positive relationship exists between non-black suburban poverty and Black suburbanization, as displayed in Appendix Figure A.4. There should be no mechanical relationship between non-black suburban poverty and Black suburbanization. These results therefore suggest that increasing poverty within suburban areas is related to Black suburbanization, and is not simply due to a mechanical effect involving poorer Black residents moving to the suburbs.

It is possible that factors that are not included in our regression drive the relationship between Black suburbanization and suburban poverty. For example, if Black families chose to move into suburban areas that were already becoming poorer, perhaps because those areas were more affordable, then the relationship discussed above could exist even if changes in poverty were not directly related to the growth in the Black suburban population. We use an instrumental variables strategy, discussed in more detail in Section 4, to address these concerns.

Finally, one may wonder why we have found evidence that suburban poverty and Black suburbanization are related. In the following section, we turn to economic theory to provide an explanation for this phenomenon.

3 Model

In this section we provide a theoretical justification for why Black suburbanization may have changed the geographic distribution of non-black poverty. Our model demonstrates that an increase in the number of Black suburban residents can lead poorer non-black residents to move to those same suburbs. Individual preferences for sorting based on income and race rationalize this behavior as a spatial equilibrium.

3.1 Model setup

We base our model on Banzhaf and Walsh (2013)'s model of segregation and Tiebout sorting. In their model, residents of a metropolitan area choose where to live based on both demographics and preferences for public goods. To this, we add an additional jurisdiction (suburb), endogenize the quality of the public good, and alter the housing supply to be perfectly elastic instead of perfectly inelastic. Our additions allow the model to predict suburban residential patterns more accurately.

Our model has three jurisdictions, which we refer to as $j \in \{C, S_1, S_2\}$, representing one city and two suburbs. Housing supply in each jurisdiction is perfectly elastic at price p^j. Individuals pay property taxes on their housing, and the quality of the jurisdiction's public good is proportional to the revenue from property taxes.

The remainder of the setup follows Banzhaf and Walsh (2013), except where noted. We normalize the price of housing in jurisdiction C, p^C, to zero. Each individual i is a member of a demographic group $r \in \{b, w\}$, where group b has measure 0.25 and group w has measure 0.75. We use a Cobb-Douglas utility function with an expenditure share of $\alpha = 0.75$ on consumption, where consumption equals income minus taxes and the cost of housing. Utility for individual i from group r in jurisdiction j is given by:

$$U_{i,r}^j(Y_i, p^j) = (Y_i - (1+t)\, p^j)^\alpha \, (tp^j + D_r^j)^{1-\alpha} \tag{1}$$

where Y_i is individual i's income and D_r^j reflects group-specific tastes for demographic composition. Individual income Y_i comes from a group-specific income distribution: $Y_w \sim \text{Uniform}(0, 1.1)$ and $Y_b \sim \text{Uniform}(0, 1)$. We add a property tax, at rate $t = 0.01$, where tp^j captures the quality of the public good in jurisdiction j.

Our functional form for D_r^j is very similar to in Banzhaf and Walsh (2013), though changed to ensure a non-negative value. This functional form is based on a "bliss point" for demographic composition, with parameters taken from previous literature. D_r^j is maximized at a certain demographic composition (the bliss point), and decreases as the demographic composition of one's jurisdiction deviates from this point. Specifically, letting s_w^j denote the share of residents of jurisdiction j that belong to group w, we set

$$D_r^j = \begin{cases} 1 - (s_w^j - 0.9)^2 \text{ if } r = w \\ 1 - (s_w^j - 0.5)^2 \text{ if } r = b \end{cases}$$

Equilibrium is given by an allocation of individuals and housing prices across jurisdictions such that each individual resides in his or her preferred jurisdiction given the prevailing prices and choices of other individuals. In their model with two jurisdictions, Banzhaf and Walsh (2013) prove that residents are segregated by r in all stable equilibria if the difference in public good quality between jurisdictions is small. If the difference in public good quality between jurisdictions is large, residents are integrated by r but segregated by income in the stable equilibrium. These findings illustrate the trade-off between preferences for demographic composition and public good quality in this model.

3.2 Model results

We describe two equilibrium allocations that we obtained from simulating this model of residential choice with 1,000 individuals[7].

3.2.1 Equilibrium one: segregated suburbs

In the first equilibrium, the city is split equally between residents of groups b and w while only members of group w live in the suburbs. Suburban housing prices that can support this equilibrium are $p^{S_1} = 0.0198, p^{S_2} = 0.0198$.

In this equilibrium, the poorest residents of the metropolitan area all live in the city. Nevertheless, the city is home to some wealthier residents as well (especially from group b, all of whom live in the city). The average income in the suburbs is higher than in the city in

[7]This model has multiple equilibria. We describe the two equilibria that we found, but note that there may be more equilibria that we did not find. However, we believe that rich Black and poor White residents live in the same jurisdiction in all racially integrated equilibria.

this equilibrium, as evidenced in the income distribution in both the model and its empirical counterpart in Figure 4. Recall that only members of group w live in the suburbs, though the poorest members of group w live in the city.

This equilibrium is reminiscent of the structure of American metropolitan areas before the Fair Housing Act. Though in this model members of group b chose to live in the city, historically Black families faced pressure to live in cities while wealthier White families lived in segregated suburbs (Rothstein 2017).

We compare the income distribution from the model with the empirical income distribution of Chicago's urban and suburban areas[8] from the 1990 Decennial Census. The data for this exercise is discussed in more detail in Section 2. Examining the empirical income distribution, we find that there is a higher frequency of lower income individuals in the city than in the suburbs and a higher frequency of higher-income individuals in the suburbs than in the city. The model and empirical results are consistent in this regard. However, the model features more extreme income segregation across areas than does the empirical income distribution: there are wealthier White residents in the city, and poorer White residents in the suburbs, than the model predicts. Additionally, unlike in the model, incomes among the Black population are not uniformly distributed.

[8] We create the empirical income distributions using one metropolitan area because the model is also of a single metropolitan area. Income differences between metropolitan areas make the empirical distributions more difficult to analyze if we include more than one metropolitan area

Figure 4: Income distribution in the first equilibrium

Note: An equilibrium from our modeling exercise is presented on the left. On the right, we use household income data from the 1990 decennial Census for all urban and suburban census tracts in the Chicago metropolitan area.

3.2.2 Equilibrium two: integrated suburbs

In the second equilibrium, the suburbs are more integrated along demographic lines but are stratified by income. Housing prices that support this equilibrium are $p^{S_1} = 0.0053, p^{S_2} = 0.0216$.

In this equilibrium, wealthier residents pay to live in the suburbs because both groups find the demographic composition in at least one suburban jurisdiction preferable to the demographic composition of the city. The poorest residents maximize their utility by choosing the lower cost of housing that the city offers.

A contingent of poorer residents of group w, who have income below 0.3, now lives in the suburbs (specifically, the first suburb, alongside wealthier members of group b) in this equilibrium. These residents are poorer than suburban residents in the first equilibrium, in which all suburban incomes were above 0.35. The first suburb is relatively integrated along demographic lines in this equilibrium, which members of group b find attractive. In fact, the wealthiest members of group b all live in suburb one - along with poorer members of group w. Figure 5 presents the bimodal distribution of income in suburb one, and the more uniform (though censored) distribution of income in suburb two, in this equilibrium.

In the second suburb, higher housing prices deter the poorest residents. However, there are some individuals with income below 0.35 who live in this suburb. All residents of this suburb, including these poorer residents, are members of group w.

We compare these model predictions with the income distribution in Chicago from the 2015-2019 five-year American Community Survey (ACS), classifying "poor suburbs" as suburban census tracts with a poverty rate of 7% or higher and all other suburban tracts as "rich suburbs". We again find that the empirical distributions have less income segregation than the predictions from the model. However, the higher density of poorer individuals in the "poor suburb" (suburb one) and of wealthier individuals in the "rich suburb" (suburb two) match the predictions of the model. Unlike in the model, though, there are wealthier individuals who live in the city, and some wealthy White individuals and poorer Black individuals who live in the poorer suburb. Like in the model, some impoverished individuals live in the richer suburb, though it primarily consists of wealthy White residents.

Figure 5: Income distribution in the second equilibrium

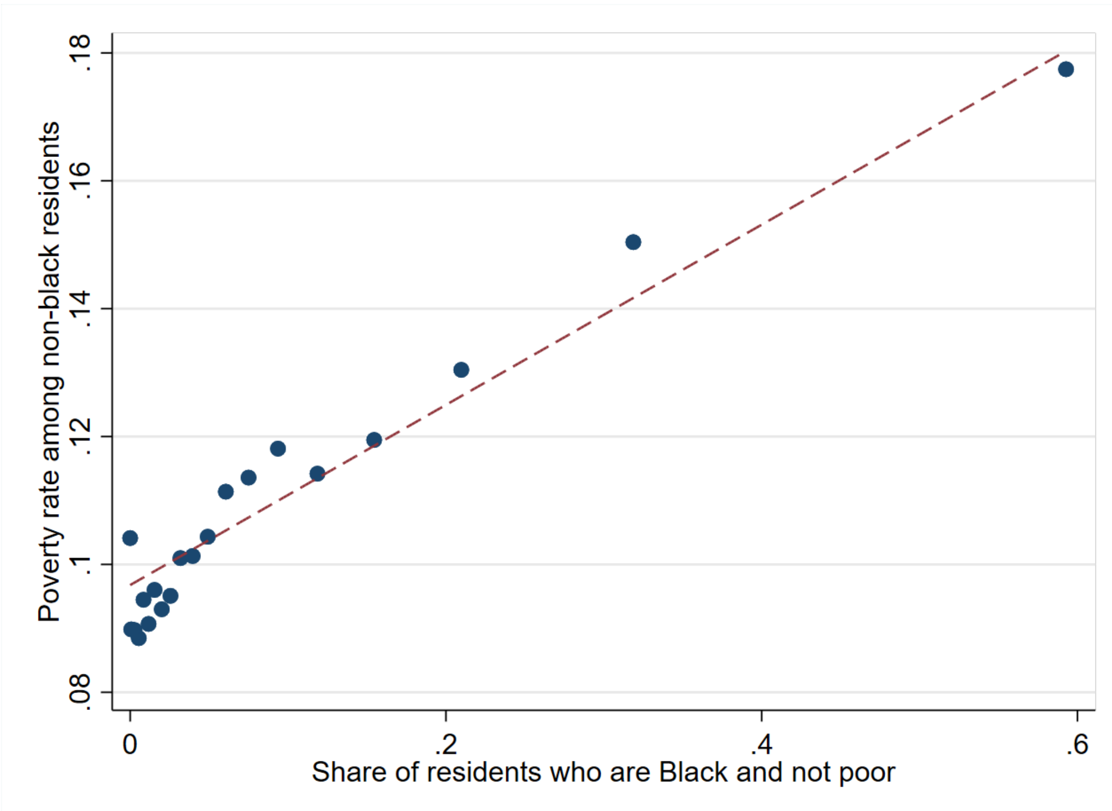
Note: An equilibrium from our modeling exercise is presented on the left. On the right, we use household income data from the 2015-2019 five-year ACS for all urban and suburban census tracts in the Chicago metropolitan area. Frequencies for the Black population in the Chicago area use the scale on the right-hand side for ease of visibility.

3.3 Implications

The results of this simple model demonstrate how suburbanization of one group can lead to increases in suburban poverty, and expose relatively well-off members of the suburbanizing group to the poorer members of the other group, even if the overall poverty rate remains constant. The migration of members of group b to the suburbs leads to a new equilibrium in which wealthier residents of group b and poorer members of group w live in suburb one. Since members of group w do not prefer this demographic composition, housing prices are low in suburb one in this equilibrium. This affordability leads some of the poorest members of group w to choose to live there. Taken together, these theoretical results indicate that demographically-influenced movement of the White suburban population between jurisdictions and changes in housing prices may be important mechanisms by which Black suburbanization and suburban poverty are related.

One prediction of our model is that wealthier Black residents may live in the same suburban areas as poorer non-black residents. This prediction is evident in American suburbs in the 2015-2019 ACS. As shown in Figure 6, our census tract-level data shows that the poverty rate among non-black suburban residents increases with the share of the tract population consisting of non-poor Black residents.

Figure 6: Poor non-black residents live with non-poor Black residents in the suburbs



Note: Tract-level binscatter of the poverty rate among non-black residents on the share of the population that is Black and not poor, for all suburban census tracts. All variables are measured using the 2015-2019 five-year ACS. Data from 27,084 suburban census tracts included in this figure.

A second prediction of our model is that there will be wealthy suburbs that remain largely segregated by race, and that some impoverished White residents will also live in these suburbs. These predictions are borne out in the Chicago area, as evidenced in the distribution of race and income in "Suburb 2" in Figure 5.

Our model has several implications for understanding suburban poverty. First, there is a straightforward theoretical justification, operating through changes in home prices and movement of the non-black population between jurisdictions, by which suburbs become poorer in response to Black suburbanization, and by which Black suburban residents encounter increased poverty. Second, declining home prices may attract poorer residents, strain municipal finances and impact public good provision in certain suburbs.

Though we now know the theoretical rationale for why suburbanization of middle-income Blacks residents may change the metropolitan area's geographic distribution of poverty, we do not know the magnitude of the relationship. Since the model involves stratification by race and income, it delivers predictions in which small movements of one group can lead to large responses of another group. Knowing the size of this relationship, empirically, will illuminate how much we expect the geographic distribution of poverty to change, and suburban Black residents' poverty exposure to increase. Determining appropriate policy responses, such as changes in funding for local governments or public goods, depends on determining the size of this relationship.

4 Empirical Strategy

We want to determine the extent to which the geographic distribution of poverty changes in response to Black suburbanization. That is, we want to estimate β in the causal model given by equation 2. In this equation, y_i is the share of the impoverished population of MSA i that lives in the suburbs and x_i is the Black share of the suburban population of MSA i. We will later examine additional outcomes, denoted $\tilde{y}_i$, including the share of the impoverished non-black population of MSA i that lives in the suburbs. This estimation will also tell us the extent to which Black suburban residents are disproportionately exposed to the increase in suburban poverty.

$$\Delta_{1990,2015}\, y_i = \alpha + \beta \Delta_{1990,2015}\, x_i + \varepsilon_i \tag{2}$$

If $\Delta_{1990,2015}\, x_i$ and ε_i are not orthogonal, then estimating β using OLS will not reveal the true causal relationship. Our primary concern is that Black individuals decided whether or not to suburbanize based on their predictions about the evolution of poverty in the suburbs. For example, if Black families in a given MSA chose to suburbanize more because the suburban areas of that MSA had smaller increases in poverty, then $\Delta_{1990,2015}\, x_i$ and ε_i would be negatively correlated, biasing the OLS estimate of β.

To address these endogeneity concerns and estimate the causal relationship, we develop a shift-share instrument for the change in the Black share of the suburban population between 1990 and 2015-2019. As in Boustan (2010), Derenoncourt (2022), and Cui (2024), our shift-share instrument uses variation induced by the Great Migration of four million Black individuals from the South to Northern[9] cities between 1940 and 1970. We build on these

[9] Here, and throughout the text, Northern refers to any area outside of the South.

existing empirical strategies by incorporating the distance from the predominant urban Black neighborhood to the nearest suburb into our instrument. Validity of this instrument relies on exogeneity of the shocks: shocks to the Southern counties that Black individuals left between 1940 and 1970 should be unrelated to unobserved determinants of changes in contemporary Northern suburban poverty.

The regression model that we bring to the data is below, where we construct z_i as an instrument for $\Delta_{1990,2015} x_i$. We include a small set of control variables $\mathbf{c_i}$ to reduce the variation in ε_i. Letting $\varepsilon_i = \gamma \mathbf{c_i} + \epsilon_i$, we control for MSA population in 1990 and Census Region fixed effects, following Boustan (2010). Controlling for population and region allows us to analyze the suburbanization of poverty among cities that we broadly expect to have similar spatial structure. The regression model that we bring to the data is therefore:

$$\Delta_{1990,2015}\, y_i = \alpha + \beta \Delta_{1990,2015}\, x_i + \gamma \mathbf{c_i} + \epsilon_i \tag{3}$$

4.1 Constructing our shift-share instrument

We build our shift-share instrument for $\Delta_{1990,2015}\, x_i$ by using variation in the strength of migrant networks between Northern cities and Southern counties in 1940 and variation in the amount of Black out-migration across Southern counties between 1940 and 1970. We augment this standard instrument by weighting the value for each MSA by the inverse of the distance between the largest urban Black neighborhood and the nearest suburb. These sources of variation allow us to predict growth in the Black suburban population in each Northern city between 1990 and 2015-2019 that we argue is unrelated to contemporary economic conditions.

We construct the shift-share instrument z_i for the change in the Black share of the suburban population of MSA i as follows:

$$z_i = \sum_k e_i s_{ik} g_k \tag{4}$$

where, following the notation of Borusyak et al. (2022), e_i is our regression weight for the inverse distance between the largest urban Black neighborhood and the nearest suburb in MSA i, s_{ik} (share) is the share of the Black migrant population of MSA i in 1940 that lived in county k in 1935, and g_k (shift, or shock) is the growth in predicted Black net out-migration from county k between 1940 and 1970. We discuss each element of z_i in turn, saving our discussion of the regression weight e_i for last.

We use the 1940 full count Census to calculate the shares s_{ik}. The 1940 full count Census records where Black migrants who moved to Northern cities lived in both 1935 and 1940.

We define

$$s_{ik} = \frac{\text{Number of Black migrants from } k \text{ to } i \text{ between 1935 and 1940}}{\text{Total number of Black migrants to } i \text{ between 1935 and 1940}} \tag{5}$$

The shocks g_k measure the growth in predicted Black net out-migration from each county k. We use predicted migration instead of realized migration to isolate the impact of county-level push factors on migration from the impact of Northern pull factors. We predict net out-migration following the approach of Boustan (2010) and Derenoncourt (2022), by regressing the county-level Black net out-migration rate for each decade t between 1940 and 1970 on county characteristics. Data on county characteristics and Black net out-migration rates come from Boustan (2016). We use the same vector of decade-specific county characteristics X_{kt} as Boustan (2010), and run the following regression:

$$\text{Black net out-migration rate}_{kt} = \alpha + \beta X_{kt} + \omega_{kt} \tag{6}$$

We then use the estimated coefficients to predict Black net out-migration rates:

$$\text{Predicted Black net out-migration rate}_{kt} = \hat{\alpha} + \hat{\beta} X_{kt} \tag{7}$$

The shocks g_k are then defined as the predicted amount of Black net out-migration from county k between 1940 and 1970 from equation 7, divided by the number of Black migrants leaving from k between 1935 and 1940. That is,

$$g_k = \frac{\text{Predicted number of Black net out-migrants from } k \text{ between 1940 and 1970}}{\text{Number of Black out-migrants from } k \text{ between 1935 and 1940}} \tag{8}$$

In Appendix Table A.6, we use Boston and Cleveland to provide a simplified example of how we combine the shifts and shocks to construct z_i. In this table, we set $e_i = 1$ and use a simplified version of the shocks g_k. We display the share s_{ik} for the top origin counties k for each city. In this example, we measure g_k as the percent growth in the amount of Black net out-migration from the given county between 1940 and 1970. Negative numbers represent net black in-migration. Computing the instrument z_i for each city as the weighted average of growth in migration $\sum_k s_{ik} g_k$, we predict the Black share of the suburban population will increase more in Cleveland than in Boston – which is indeed what happened. This pattern exists in more than just these two cities, as we show in our analysis of the first stage of the instrument below.

To strengthen our instrument, we use the regression weight e_i as a measure of the inverse of the distance to the suburbs. All else equal, we expect MSAs in which the suburbs are closer to the predominant urban Black neighborhood to have a bigger increase in the Black suburban population. This is because Black suburbanization often began in the suburbs close to urban areas in which Black migrants settled during the Great Migration (Wiese 2019). For each MSA i, we measure the distance d_i from the center of the largest urban Black neighborhood to the nearest suburb. We describe how we measure this distance in more detail in Appendix A.3.2. Our regression weight is then $e_i = d_i^{-1}$.

4.2 Instrument Validity

The recent econometric literature on shift-share instruments provides three recommendations for conducting correct inference using these instruments.

First, identification for shift-share instruments can come from either exogenous shocks or exogenous shares. Our instrument for Black suburbanization relies on exogenous shocks, and satisfies the exclusion restriction if our shocks are conditionally exogenous. Specifically, the shocks g_k, which measure the growth in predicted Black net out-migration from Southern counties, must be unrelated to weighted unobserved determinants of changes in poverty in Northern suburbs (Borusyak et al. 2022).

We write the exclusion restriction at the level of the shocks, because our estimating equation is the shock-level regression equation 11 described below. Our exclusion restriction, equation 9, means that county-level migration shocks g_k must be orthogonal to MSA-level unobservables[10]. For example, there should not be systematic differences between the unobserved determinants of suburban poverty in Northern MSAs that have strong migrant-network connections to Southern counties with low versus high growth in predicted black net out-migration.

$$\mathbb{E}\left[\sum_k g_k \, s_k \tilde{\varepsilon}_k\right] = 0 \tag{9}$$

Though we cannot explicitly test the exclusion restriction, we conduct a pre-trends test, as recommended by Borusyak et al. (2022), in which we replace our main outcome variable with the outcome for the period prior to our analysis. We estimate equation 10, instrumenting for x_i with z_i[11]. A statistically significant coefficient δ would indicate that our instrument is correlated with an unobserved confounding variable, violating the exclusion restriction.

$$\Delta_{1980,1990} \, y_i = \alpha + \delta \Delta_{1990,2015} \, x_i + \gamma \mathbf{c_i} + \epsilon_i \tag{10}$$

[10] These unobservable characteristics ε_i are transformed to the shock level and weighted by exposure shares to become $\tilde{\varepsilon}_k$. See the Appendix for details on this transformation, or refer to Borusyak et al. (2022).

[11] We estimate this equation at the shock level, as explained below.

The results of the pre-trends test support the validity of our instrument for Black suburbanization. In column two we control for MSA population in 1990 and Census Region fixed effects, following Boustan (2010). In column three we use MSA population weights. Regardless of whether we include these control variables and weights, the estimates of δ in Table 1 are not statistically significant. In addition to lacking statistical significance, these coefficients are also approximately one order of magnitude smaller than in our main results.[12]

Table 1: Pre-trends test

	Change in suburban poverty 1980-1990		
	(1)	(2)	(3)
Change in suburban Black share	-0.163	-0.215	0.273
	(0.195)	(0.332)	(0.430)
Observations	1174	1174	1174
Control Variables	No	Yes	Yes
Population Weighting	No	No	Yes
Effective F-statistic for IV	18.8	20.6	10.2

Note: Exposure robust standard errors are clustered at the shock (Southern county) level. The dependent variable is the change in the share of the poor population of the MSA that lives in the suburbs between 1980 and 1990. The independent variable is the change in the suburban Black share between 1990 and 2015. Control variables at the MSA level are total population in 1990 and Census Region fixed effects. All columns of this table include a regression weighting e_i for inverse distance to the suburbs. Results using the instrument without this weight are in Appendix Table A.7.

Second, Borusyak et al. (2022) suggest estimating shift-share coefficients at the level of the shocks to obtain correct standard errors[13]. We follow their suggestion with our sample of 1,174 Southern counties[14], as described below. Therefore, the unit of observation in our

[12]Borusyak et al. (2022) also suggest testing the control variables for balance by using them as the dependent variables in equation 10. Doing so, we detect imbalance in our West and Midwest Census Region dummies. However, the authors note that this imbalance may not lead to bias if the regression coefficients are robust to including these controls. As we will see, the interpretation of our coefficients is not sensitive to the inclusion of these controls.

[13]Both Borusyak et al. (2022) and Adao et al. (2019) show that conventional standard errors may be invalid because observations with similar values of the shares s_{ik} may have correlated residuals.

[14]As suggested by Borusyak et al. (2022), we compute the inverse of the Herfindahl index of the exposure shares to measure the effective sample size of this regression. Though our sample includes 1,174 counties, our effective sample size using county-level shocks is 142.

regressions are Southern counties that sent black migrants to Northern MSAs. There are 97 Northern MSAs represented in this sample.

To estimate the shock-level regression, we convert our MSA-level measures of changes in suburban poverty and Black suburbanization from equation 3 to the level of the shocks[15]. We then estimate the following shock-level regression using regression weights $s_k = \sum_i e_i s_{ik}$ and instrument g_k (the shocks) to generate our main results:

$$\bar{y}_k^{\perp} = \alpha + \beta \bar{x}_k^{\perp} + \bar{\varepsilon}_k^{\perp} \tag{11}$$

Though we obtain our results from estimating the shock-level equation 11, the point estimate of β is equivalent to that from using a standard shift-share instrument in the MSA-level regression equation 3 (Borusyak et al. 2022). Therefore, our estimates of β can be interpreted at the MSA level, and reflect the magnitude of the increase in suburban poverty resulting from a one percentage point increase in the Black share of the suburban population.

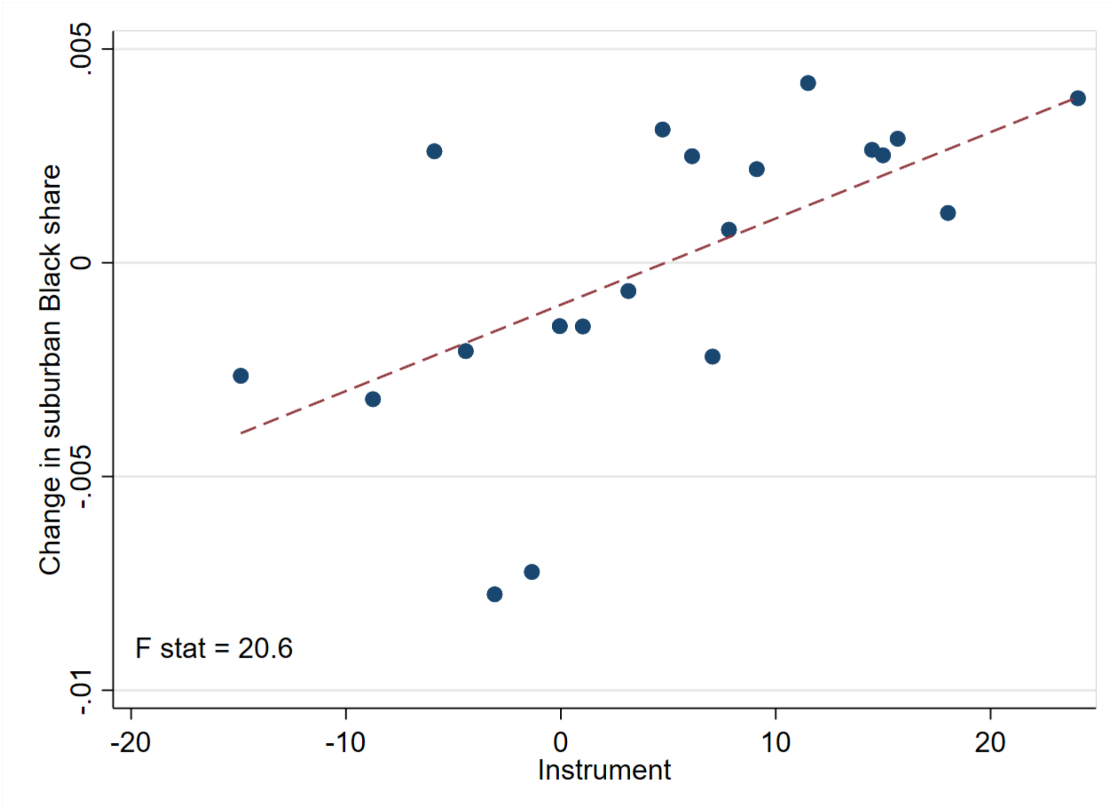
Finally, Borusyak et al. (2022) note that if the sum of weighted exposure shares $\sum_k e_i s_{ik}$ is not constant across locations i, one must control for the sum of these shares in the regression. Therefore, we control for the sum of exposure shares, $\sum_k e_i s_{ik} = \sum_k s_{ik}/d_i$, in our regressions. We adjust the exposure shares to account for our regression weight e_i, the inverse of the distance to the suburbs. For a given MSA, the sum of these weighted exposure shares is the fraction of all Black migrants to that MSA that came from Southern counties, weighted by the inverse of the distance from the largest urban Black neighborhood to the suburbs.

4.3 First-stage

Our instrument needs a strong first-stage relationship to provide identification. As displayed in the shock-level binscatter Figure 7, our instrument z_i can indeed predict changes in Black suburbanization between 1990 and 2015-2019. Our instrument has a positive and statistically significant relationship with Black suburbanization. F-statistics for each specification are included in our tables of results.

[15] In practice, we use the Stata program *ssaggregate* to do so, converting x_i and y_i to $\bar{x}_k^{\perp}$ and $\bar{y}_k^{\perp}$. See the Appendix or Borusyak et al. (2022) for more details.

Figure 7: First stage on Black suburbanization



Note: Binscatter at the shock (Southern county) level. The dependent variable is the change in the suburban Black share between 1990 and 2015, which is converted to the shock level and regressed against our shock-level instrument. This figure includes data from 1,174 counties.

5 Results

Using the shift-share instrument described above, we find that poverty shifts to the suburbs of metropolitan areas in response to Black suburbanization, disproportionately exposing Black suburban residents to the change in the location of poverty. Both overall suburban poverty and non-black suburban poverty significantly increase in response to an increase in the Black share of the suburban population.

In Table 2 we display our results from estimating equation 11, a shock-level IV regression of the change in suburban poverty on the change in the Black share of the suburban population. We control for the sum of exposure shares in each specification. Though the coefficients vary depending on whether we control for the MSA's population and Census Region or weight each MSA by population, the estimated coefficients remain positive and statistically significant throughout. In Appendix Table A.8, we set $e_i = 1$ and use the instrument that does not account for the distance to the suburbs. The F-statistic is higher when we include the suburban-distance regression weighting $e_i = d_i^{-1}$. The results are still significant when clustering the exposure-robust standard errors at the state, instead of county, level (Appendix Table **??**).

Table 2: Black suburbanization and suburban poverty

	Change in suburban poverty		
	(1)	(2)	(3)
Change in suburban Black share	1.795***	2.345***	3.657***
	(0.316)	(0.494)	(1.079)
Observations	1174	1174	1174
Control Variables	No	Yes	Yes
Suburban Distance Weighting	Yes	Yes	Yes
Population Weighting	No	No	Yes
Effective F-statistic for IV	18.8	20.6	10.2

Note: Exposure robust standard errors are clustered at the shock (Southern county) level. The dependent variable is the change in the share of the poor population of the MSA that lives in the suburbs. The independent variable is the change in the suburban Black share between 1990 and 2015. Control variables at the MSA level are total population in 1990 and Census Region fixed effects. Regressions weights in column three are based on MSA population in 1990. In Appendix Table A.8, we set $e_i = 1$ and use the instrument that does not account for the distance to the suburbs. *** indicates significance at the 1% level.

Given the units, the interpretation of these coefficients is that a one percentage point increase in the Black share of the suburban population caused the share of the total impoverished metropolitan population that lives in the suburbs to increase by approximately two percentage points (2.3 percentage points in our preferred specification). These coefficients remain significant if we cluster our standard errors at the state instead of county level.

Our results indicate that large shifts in the metropolitan-area distribution of poverty result from Black suburbanization. The coefficients in Table 2 imply that the mean increase in the Black share of the suburban population (2.2 percentage points) caused an increase in the share of the metropolitan-area poor population that lives in the suburbs of $2.2 * 2.345 = 5.16$ percentage points, which is approximately $\frac{3}{4}$ of the mean increase in suburban poverty of 6.5 percentage points.

To remove any mechanical effects by which Black suburban residents increased suburban poverty, we next examine the effects of Black suburbanization on non-black suburban poverty and find that non-black suburban poverty increased as a result of Black suburbanization as well. To estimate these regressions, we replace y_i from the our main regressions with $\tilde{y}_i$, measuring suburban poverty among the non-black suburban population. The coefficients in Table 3 are approximately half the size of the coefficients in Table 2, but remain statistically significant. Our results show that a one percentage point increase in the Black share of the suburban population caused the share of the poor non-black population that lives in the suburbs to increase by approximately one percentage point. The results in columns one and two are still significant when clustering the exposure-robust standard errors at the state, instead of county, level, though the coefficient in column three loses significance (Appendix Table A.10).

Table 3: Black suburbanization and non-black suburban poverty

	Change in non-black suburban poverty		
	(1)	(2)	(3)
Change in suburban Black share	0.982***	1.285***	1.731*
	(0.285)	(0.459)	(1.007)
Observations	1174	1174	1174
Control Variables	No	Yes	Yes
Suburban Distance Weighting	Yes	Yes	Yes
Population Weighting	No	No	Yes
Effective F-statistic for IV	17.7	20.1	7.8

Note: Exposure robust standard errors are clustered at the shock (Southern county) level. The dependent variable is the change in the share of the poor non-black population of the MSA that lives in the suburbs. The independent variable is the change in the suburban Black share between 1990 and 2015. Control variables at the MSA level are total population in 1990 and Census Region fixed effects. Regressions weights in column three are based on MSA population in 1990. In Appendix Table A.8, we set $e_i = 1$ and use the instrument that does not account for the distance to the suburbs. *** indicates significance at the 1% level.

Our results indicate that poverty among non-black residents shifted to suburban areas in MSA in which more Black residents also moved to the suburbs. Further, these results quantify the undue exposure to suburban poverty that Black suburban residents face. These coefficients indicate that, in an MSA with the average increase in the Black share of the suburban population (2.2 percentage points), Black families moved into suburban areas in which the share of the non-black poor population that lived there was $1.285 * 2.2 = 2.8$ percentage points higher than it would have been if there were no relationship between Black suburbanization and suburban poverty.

Finally, we note that the IV coefficients are consistently larger than the OLS coefficients. The relevant coefficients using OLS are 1.21 for column two of Table 2 and 0.60 for column two of Table 3. These OLS coefficients are approximately half of the size of the corresponding IV coefficients, indicating that omitted variables bias shrank the OLS coefficients towards zero. One explanation for this downward bias is that Black suburbanites endogenously choose suburbs that subsequently experienced relatively smaller increases in poverty.

6 Mechanisms: Neighborhood Change

We now investigate the mechanisms by which Black suburbanization changed the geographic distribution of poverty. Our theoretical model demonstrated how demographic tastes, changes in home prices, and the relocation of poorer individuals between the city and suburbs can increase in poverty in suburban areas into which Black residents moved. In this section, we examine these mechanisms empirically and chronicle the resulting change in suburban demographics.

6.1 Wealthier residents depart

We find that incumbent suburban residents respond to Black suburbanization by leaving the suburbs. In our model, wealthy non-black residents live in different jurisdictions from the Black residents (wealthy or not). Empirically, we test whether wealthy suburban residents departed from the suburbs in response to Black suburbanization.

We conduct our empirical tests by estimating equation 3 using different dependent variables $\tilde{y}_i$ for each subsection. We estimate these regressions by running shock-level regressions with our instrument z_i[16] as constructed in Section 4. In this subsection, our dependent variable $\tilde{y}_i$ measures the share of the non-poor population of MSA i that lives in the suburbs. Our data for $\tilde{y}_i$ comes from the 1990 decennial Census and 2015-2019 ACS.

Our results in Table 4 indicate that Black suburbanization causes the proportion of the non-poor metropolitan population that lives in the suburbs to decline. The independent and dependent variables in this regression are both shares, so the magnitude of the coefficient in

[16] Results without using our inverse distance to the suburbs weight e_i are available in the Appendix.

column two implies that a one percentage point increase in the Black share of the suburbs causes the share of the non-poor population that lives in the suburbs to decrease by 0.259 percentage points. These results indicate that wealthier suburban residents left the suburbs as Black residents moved in.

Table 4: Black suburbanization and wealthy suburbanites

	Change in suburban non-poor		
	(1)	(2)	(3)
Change in suburban Black share	-0.176***	-0.259***	-0.359***
	(0.061)	(0.068)	(0.115)
Observations	1174	1174	1174
Control Variables	No	Yes	Yes
Suburban Distance Weighting	Yes	Yes	Yes
Population Weighting	No	No	Yes
Effective F-statistic for IV	18.8	20.6	10.2

Note: Exposure robust standard errors are clustered at the shock (Southern county) level. The dependent variable is the change in the share of the non-poor population of the MSA that lives in the suburbs. The independent variable is the change in the suburban Black share between 1990 and 2015. Control variables at the MSA level are total population in 1990 and Census Region fixed effects. *** indicates significance at the 1% level.

6.2 Affordable homes decrease in price

Research on other historic episodes of Black migration has demonstrated that home prices tend to decrease with Black in-migration (Daepp, Hsu, et al. 2023). Therefore, we use our instrument to investigate the effect of Black movement to the suburbs on suburban home prices. Since we documented that the share of the non-poor population that lives in the suburbs declines with Black suburbanization, we may expect demand for suburban housing and home prices to decline as well. Given our focus on poverty, we examine changes in the bottom quartile of the suburban home price distribution.

In this analysis, our dependent variable $\tilde{y}$ is the percent change between 1990 and 2015-2019 in the 25^{th} percentile of the suburban home price distribution. Our data for this analysis comes from the 1990 decennial census and 2015-2019 ACS. For each MSA, we use tract-level median home prices to compute the value at the 25^{th} percentile of the suburban home price distribution. $\tilde{y}_i$ is then the percent change in this value between 1990 and 2015-2019. We estimate equation 3 the same way as in the previous subsection, but with this new $\tilde{y}$.

Table 5: Black suburbanization and suburban home prices (25th percentile)

	Growth in 25th percentile of suburban home prices		
	(1)	(2)	(3)
Change in suburban Black share	-19.539***	-13.780**	-17.637
	(5.122)	(5.651)	(15.722)
Observations	1174	1174	1174
Control Variables	No	Yes	Yes
Suburban Distance Weighting	Yes	Yes	Yes
Population Weighting	No	No	Yes
Effective F-statistic for IV	17.7	19.2	5.6

Note: Exposure robust standard errors are clustered at the shock (Southern county) level. The dependent variable is the percent growth in home prices at the 25th percentile of the suburban home price distribution for each MSA. The independent variable is the change in the suburban Black share between 1990 and 2015. Control variables at the MSA level are total population in 1990 and Census Region fixed effects. *** indicates significance at the 1% level.

Our results indicate that Black suburbanization caused home prices at the 25^{th} percentile to grow less quickly. Given the units, the magnitudes of this coefficients means that a one percent increase in the suburban Black share caused home prices at the 25^{th} percentile of the suburban home price distribution to grow by 13.8% less. The coefficient in column two implies that a 2.2 percentage point increase in the Black share of the suburban population (the mean increase across MSAs in our sample) caused bottom-quartile suburban home prices to grow by 30.4% less. Given this large effect on home prices, it became possible for individuals who previously could not afford to live in the suburbs to move into the suburbs.

6.3 Entry of lower-income residents

Given the depressed growth in suburban home prices documented above, suburban areas with more Black in-migrants became relatively more affordable. We now provide suggestive evidence that lower-income individuals moved into these suburbs with new Black residents.

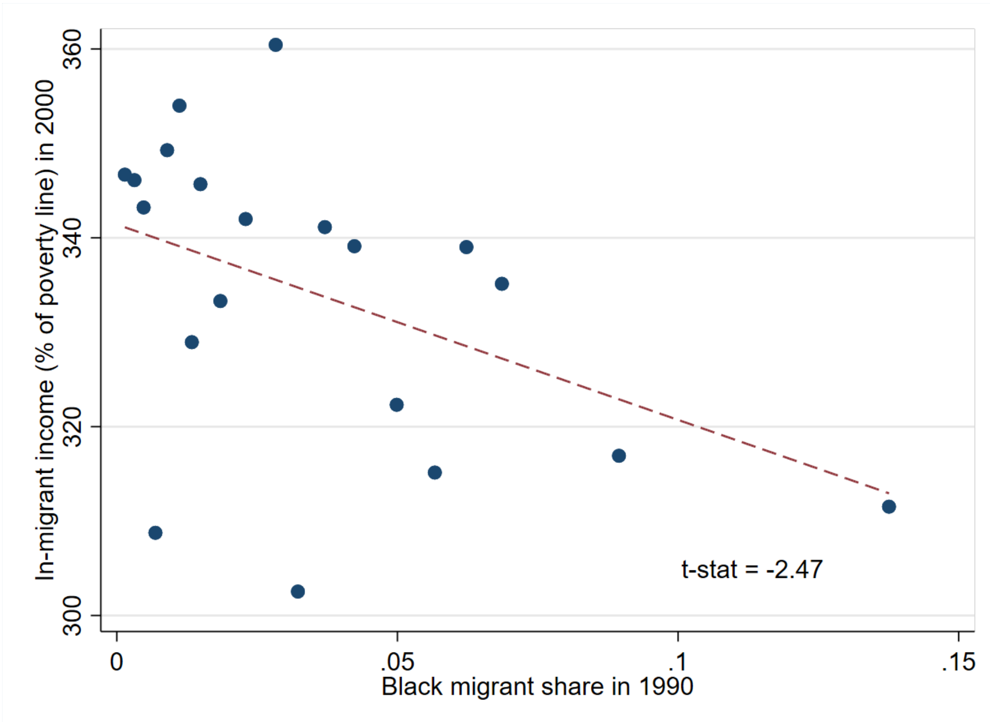
Unlike in the previous two subsections, here we need to separate incumbent suburban residents from individuals who moved into the suburbs from elsewhere. Census microdata can distinguish movers from incumbent residents, but the finest level of geography at which this data is publicly available is the Public Use Microdata Area (PUMA)[17]. Unfortunately, these coarse geographic units prevent us from distinguishing between suburban and urban PUMAs for many MSAs in our sample, limiting our ability to conduct an effective MSA-level analysis. Without being able to use our MSA-level instrument, here we present a correlational analysis instead of a causal one.

However, we do find a correlation between Black in-migration and subsequent in-migration of lower-income individuals when analyzing suburban PUMAs[18]. We use Census and ACS microdata to create our dependent variable, which is the average income of individuals who moved into suburban PUMAs between 1995 and 2000, expressed relative to the poverty line. Our independent variable is the share of residents of each suburban PUMA who were Black in-migrants in 1990. The binscatter in Figure 8 indicates that the average income of individuals who moved into suburban PUMAs decreased as the Black migrant share of the PUMA increased. Although this relationship may not be causal, it suggests that poorer individuals followed Black residents into the suburbs.

[17]PUMAs are designed to include at least 100,000 residents. Our previous analysis classified, and then aggregated, census tracts, which are designed to have approximately 4,000 residents.

[18]Our analysis in this section technically takes place at the level of the CONSPUMA, which is a PUMA with constant boundaries over time. We refer to these as PUMAs in the text for simplicity.

Figure 8: Income of movers to the suburbs decreases following Black in-migration



Note: Observations are at the CONSPUMA level, which is the smallest constant-boundary geographic unit in the publicly available microdata, for 240 suburban CONSPUMAs. The binscatter indicates that income (expressed as a percentage of the poverty line) of new suburban residents in 2000 declines as the share of CONSPUMA residents in 1990 who are new Black residents increases.

Taken together, the evidence presented in this section demonstrates that poverty suburbanized due to a process of neighborhood change: Black suburbanization leads incumbent residents who are not poor to leave the suburbs, increases the affordability of suburban housing, and facilitates the movement of lower-income residents into the suburbs.

7 Robustness

In this section, we find that our main results and the key mechanisms by which we find Black suburbanization changes the distribution of poverty within metropolitan areas are generally robust to changing the spatial scale and timing of our analysis. Additionally, we demonstrate that entry of Black residents into specific suburbs within an MSA shifts the distribution of poverty between suburbs within the MSA. We show that non-black poverty increases as a result of Black suburbanization even between suburban neighborhoods within an MSA.

7.1 Robustness to Spatial Scale: Within-MSA Analysis

With the exception of the Section 6.3, our analysis thus far has focused on changes that occur between MSAs. However, recent research (Lichter et al. 2023) suggests that some incumbent suburban residents respond to Black suburbanization by moving to different suburbs within their MSA. Therefore, in this section we analyze how home prices and poverty changed between neighborhoods within an MSA as a result of Black suburbanization.

7.1.1 Within-MSA instrument for black suburbanization

We develop a new instrument to predict changes in Black population growth between suburban neighborhoods within an MSA. This instrument helps address endogeneity concerns arising because Black households did not choose suburban destinations at random, but may have chosen neighborhoods with differential trends in home prices, for example.

To construct our instrument, we build on a nascent literature in urban economics, exemplified as Davis et al. (2024) and Sood and Almagro (2024), that makes use of the interplay between the geographic and demographic structure of cities. Our instrument is built on our empirical observation that Black residents moved out of the city and towards the suburbs in a particular direction. Specifically, we find that Black individuals tended to move from urban neighborhoods towards the suburbs in the direction away from the city center, perhaps in search of more affordable accommodations[19].

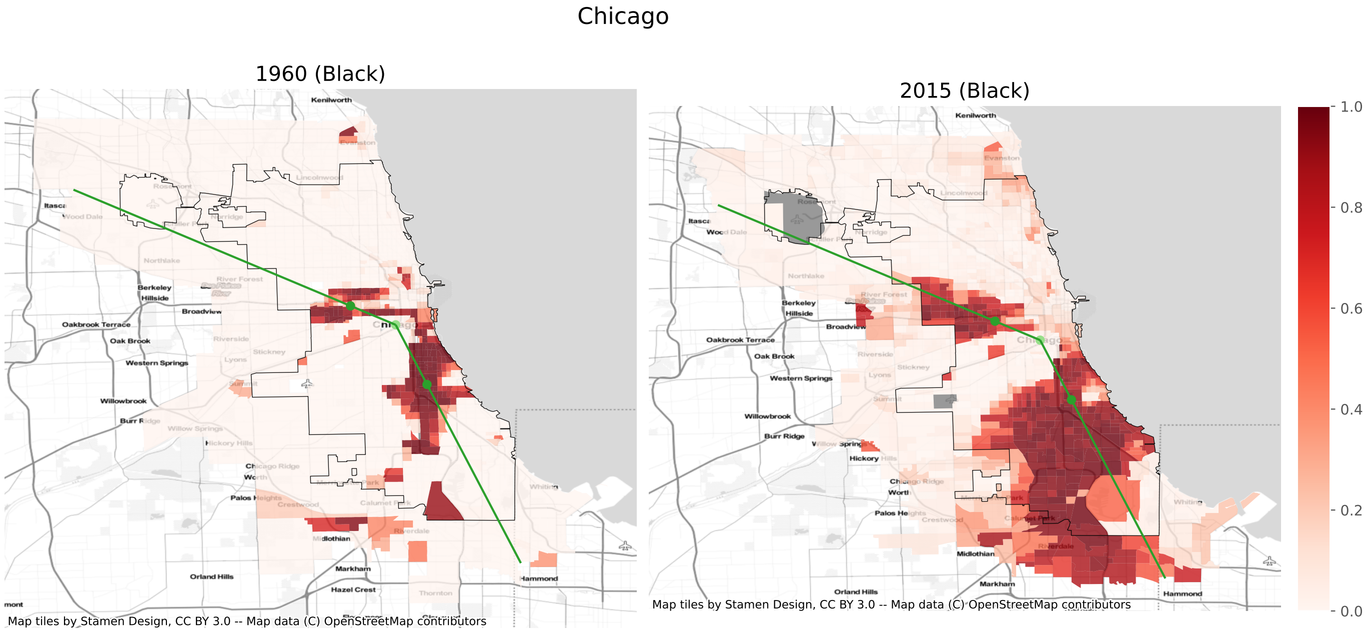
This pattern of movement allows us to use differences in the direction between suburban census tracts and the main urban Black neighborhood as an exogenous shifter of Black population growth. To construct our instrument, we draw a ray from the Central Business District (CBD) of each MSA to the center of the historic Black neighborhood(s)[20], and extend this ray out towards the suburbs. This ray represents the direction in which we predict the Black population suburbanized.

We use Chicago as an example of how we construct these rays. There were two large concentrations of the Black population in Chicago in 1960. For both of these neighborhoods, we draw a ray from the CBD to the center of the Black neighborhood, and extend it outwards. Examining the location of Black residents in the Chicago area in 1960 and 2015-2019 in Figure 9, we find that the Black population generally suburbanized in our predicted directions.

[19] Monocentric city models, such as those pioneered by Alonso (1964), predict that land further from the city center is more affordable

[20] We allow cities to have up to two Black neighborhoods, depending on the geographic dispersion of the Black population in the 1960 decennial Census. For each Black neighborhood, we find the population-weighted centroid of the group of neighboring tracts that have large Black populations in 1960. We use IPUMS NHGIS place points for the location of the CBD.

Figure 9: Direction of Suburbanization



Note: Data on the Black population at the census tract level from the 1960 decennial Census and 2015-2019 five-year ACS. Darker colors denote higher Black population shares within the tract. Chicago city boundaries denoted in black. Center of city (CBD), and center of both urban Black neighborhoods in 1960, denoted by green dots. The green ray extends out from the CBD through the center of the urban Black neighborhoods.

Once we have constructed these rays, we measure two distances for each suburban census tract: the distance from the center of the urban Black neighborhood to the point on the ray that is closest to the tract (measured along the ray), and the distance between the center of the tract and the ray. We then aggregate the tracts into groups due to the high degree of racial segregation between individual tracts. We create groups j of nearby suburban tracts within MSA i based on the urban Black neighborhood n to which the tract is closest, and use these groups of tracts[21] as our unit of analysis. Our instruments are then the average distance along the ray and the average distance to the ray.

We want to estimate how non-black poverty and home prices of suburban tract-group j in MSA i change in response to growth of the Black population x_j using the causal model of equation 12. For a given outcome y_j, we estimate β using IV regression with instrument z_j:

$$y_j = \alpha + \beta x_j + \phi_i + \varepsilon_j \tag{12}$$

[21] We created tract groups based on a k-means algorithm for geographical clustering, with approximately one dozen tracts in each group.

Our exclusion restriction with respect to outcome y_j and instrument z_j is then:

$$\mathbb{E}[z_j \times \varepsilon_j \,|\, \phi_i, c_j] = 0 \tag{13}$$

Our exclusion restrictions require that, within an MSA, the distance along the ray, from the center of the urban Black neighborhood to the closest point to the ray, must not be related to tract-group determinants of home prices or the non-black poverty rate other than through the change in the Black population share. Our method for creating this instrument, which relies solely on distance along the ray, which was in turn constructed that we constructed based on the location of the urban Black neighborhood and CBD, lends credibility to this assumption. We further assess this assumption with pre-trends tests that are reported in our tables of results.

7.1.2 Within-MSA changes in home prices

While our between-MSA analysis from Section 6.2 found that the bottom quartile of suburban home prices declined in MSAs with more Black suburbanization, we further examine this mechanism with our within-MSA analysis. Using our within-MSA instrument, we find that growth in the Black population in specific suburban areas within an MSA caused median home prices there to decline.

We estimate equation 12 to quantify the relationship between Black in-migration and suburban home prices. Here, y_j is the change between 1990 and 2015-2019 in the median home price[22] of suburban tract group j and x_j is the change between 1990 and 2015-2019 in the share of residents of tract group j who are Black. Data for these variables comes from the 1990 decennial Census and 2015-2019 ACS.

We conduct a pre-trends test on our instrument in columns one and two of Table 6 to determine whether home prices were on different trends in tract groups with higher versus lower values of the instrument prior to our time period of analysis. To conduct the test, we replace y_j with changes in median home prices between 1980 and 1990. A statistically significant coefficient in this regression would indicate that home prices were already on different trends, decreasing the validity of this empirical approach. Fortunately, our estimated coefficients are statistically insignificant and much smaller than in columns three and four.

Our regression results indicate that there is a negative relationship between the change in the Black share of the population of a suburban tract group and median home prices. The coefficients in columns three and four of Table 6 are negative and statistically significant. The magnitude of these coefficients indicates that an additional percentage point increase in

[22] We winsorize the top 0.5% of tract-level values due to large outliers.

the Black share of the population of the tract group between 1990 and 2015-2019 decreased growth in median home prices by around two percent relative to other suburban tract groups within the same MSA. These results support our contention that home prices decline due to Black suburbanization, which we now show holds even between suburban areas in the same MSA.

Table 6: Within-MSA home price changes

	Home price growth 1980-1990		Home price growth 1990-2015	
	(1)	(2)	(3)	(4)
Change in Black share 1990-2015	-0.439	-0.074	-1.970**	-2.423**
	(0.699)	(0.715)	(0.973)	(0.967)
Observations	330	330	330	330
Instrument	Distance along ray	Distance to and along ray	Distance along ray	Distance to and along ray
Control variables	Distance to ray	None	Distance to ray	None
MSA FE	Yes	Yes	Yes	Yes
Effective F-statistic for IV	19.9	10.0	19.9	10.0

Note: Observations at the suburban tract-group level. Regressions exclude suburban tracts that are far from the closest urban Black neighborhood, and those in the opposite direction from the center city. The highest 0.5% values of the dependent variable are winsorized at the tract level. The dependent variable is expressed as a percent, and the independent variable in percentage points. Conley standard errors are used in all columns. *** indicates significance at the 1% level.

7.1.3 Changes in (non-black) poverty between neighborhoods within an MSA

We next investigate whether our main MSA-level results, that non-black suburban poverty increases as Black residents move in, exists between neighborhoods within MSAs as well. Here, we estimate equation 12, with y_j as the change between 1990 and 2015-2019 in the non-black poverty rate of suburban tract group j and x_j as the change between 1990 and 2015-2019 in the share of residents of tract group j who are Black. Data for these variables comes from the 1990 decennial Census and 2015-2019 ACS.

Our regression results indicate that, even within an MSA, non-black poverty increased in the same parts of the suburbs that Black residents moved into. The coefficients in columns three and four of Table 7 are positive and statistically significant. The magnitude of these coefficients indicates that the non-black poverty rate increased by around 0.3 percentage points when the Black share of the population of a suburban tract group grew by an additional percentage point between 1990 and 2015-2019, relative to other tract groups in the same MSA.

Table 7: Within-MSA changes in non-black poverty

	Change in poverty 1980-1990		Change in poverty 1990-2015	
	(1)	(2)	(3)	(4)
Change in Black share 1990-2015	0.112*	0.101	0.292***	0.322***
	(0.063)	(0.062)	(0.078)	(0.085)
Observations	330	330	330	330
Instrument	Distance along ray	Distance to and along ray	Distance along ray	Distance to and along ray
Control variables	Distance to ray	None	Distance to ray	None
MSA FE	Yes	Yes	Yes	Yes
Effective F-statistic for IV	20.0	10.0	20.0	10.0

Note: Observations at the suburban tract-group level. Regressions exclude suburban tracts that are far from the closest urban Black neighborhood, and those in the opposite direction from the center city. The dependent variable is the non-black poverty rate, and the independent variable is expressed in percentage points. Conley standard errors are used in all columns. *** indicates significance at the 1% level.

Columns one and two display the results of our the pre-trends test. In the pre-trends test, y_j measures changes in the non-black poverty rate between 1980 and 1990. While the coefficient in columns one and two are statistically significant, they are less than half the magnitude of their contemporaneous counterparts in column three and four, with lower levels of significance as well. Though these pre-trends diminish the exogeneity of our instrument, our results indicate that non-black poverty still increased as Black families moved into these suburban neighborhoods, over and above the existing trends.

7.2 Robustness to Timing

While our analyses thus far have analyzed long differences (changes between 1990 and 2015-2019), in this section we define an "initial treatment" period and then examining how outcomes evolve in the subsequent period. We use the change in the Black population between 1990 and 2000 as our initial treatment, and then analyze how outcomes change between 2000 and 2015-2019. This type of analysis removes any mechanical effect that the Black in-migrants themselves had on outcomes during the initial period. The results of this analysis focus on changes in neighborhoods that are induced by, but not directly or mechanically affected by, the initial treatment. Results from this analysis show that suburban poverty increases following Black suburbanization.

Examining the timing of our between-MSA analysis shows that suburban poverty rose following an increase in the Black share of suburban residents, which increased Black suburban residents' exposure to poverty. We define our initial treatment as the change in the Black share of the suburbs of an MSA between 1990 and 2000. Our results, displayed in Appendix Table A.11, indicate that between 2000 and 2015-2019 the share of poor residents living in the suburbs increased by about two percentage points, and the share of non-black poor residents living in the suburbs by 1.5 percentage points, as a result of growth in the Black suburban population between 1990 and 2000. These results are all statistically significant, except for in column six, and are similar in magnitude to our main results from Table 2 and Table 3.

8 Consequences of Suburban Poverty

Increases in suburban poverty, which may especially affect the Black suburban residents who are disproportionately exposed to the increase in poverty, can affect all suburban residents. We show that an increase in poverty in the suburbs, holding total poverty fixed, can be harmful. We describe potential consequences of the increase in suburban poverty, discuss how the suburbs create poverty among incumbent residents, and briefly outline potential policy responses.

8.1 Aggregate welfare

Holding poverty constant but redistributing impoverished individuals across space can affect aggregate welfare in a few ways. First, impoverished individuals are harmed when poverty-reduction services are harder to access. Second, total property tax revenues may fall if home prices decline in areas in which poor individuals live that are particularly dependent on property tax revenue. Third, declines in local public good quality are especially damaging in areas with higher homeownership rates, such as the suburbs.

8.1.1 Spatial mistmatch between poverty and services

Many services designed to help those in poverty are provided at the local level. However, the increase in suburban poverty means that poor individuals have moved away from the urban centers where these services are best provided. Allard and Pelletier (2021) summarize research into the mismatch between the location of impoverished individuals and the location of high-quality anti-poverty services:

"Many key programs of support for low-income Americans - emergency food assistance, employment services, behavioral health services, and programs for children - are commonly delivered through community-based nonprofit or nongovernmental human service organizations. Nonprofit human service programs for low-income households receive roughly \$100 billion in public and private charitable support each year," which is similar to the budget of federal programs. However, unlike federal programs, the quality of nonprofit services varies widely across space, including between urban and suburban areas.

Suburbs face several challenges in providing high-quality poverty-reduction services. Initial federal investments in nonprofit human service programs focused on urban centers, providing them with more experience and institutional knowledge. Additionally, suburban poverty is spread across larger areas, limiting economies of scale in service provision. Finally, suburbs consist of multiple municipalities in which any given suburban municipality may not have political incentives to develop anti-poverty programs (Allard 2017).

The gap between urban and suburban anti-poverty resources is large, and growing. More than two-thirds of all nonprofit human services expenditures occur in urban areas (Allard and Pelletier 2021). The difference in expenditure levels has only increased, as the authors find that expenditure growth was higher in urban than suburban counties between 2000 and 2017, even as suburban poverty expanded.

This gap in resources translates into a gap in service quality, as documented by Allard and Pelletier (2023), who find "evidence that nonprofit health and human service provision per poor resident is less robust in suburban areas, and especially in those experiencing high rates of poverty or areas with a relatively higher share of Black residents." Though this mismatch between service need and service provision reduces welfare, we are unaware of evidence that demonstrates that living in a suburban area increases poverty duration. This remains an important area for future research.

8.1.2 Financing of local public goods

In addition to creating a mismatch between where poverty reduction programs are provided and needed, the geographic distribution of poverty can affect local government revenue. Suburban municipalities are sensitive to decreases in property values because most municipal tax revenue comes from property taxes, and local governments generally must balance their budgets (Glaeser 2013). Therefore, public good provision suffers if property values fall as poorer individuals enter municipalities that are highly dependent on property tax revenue.

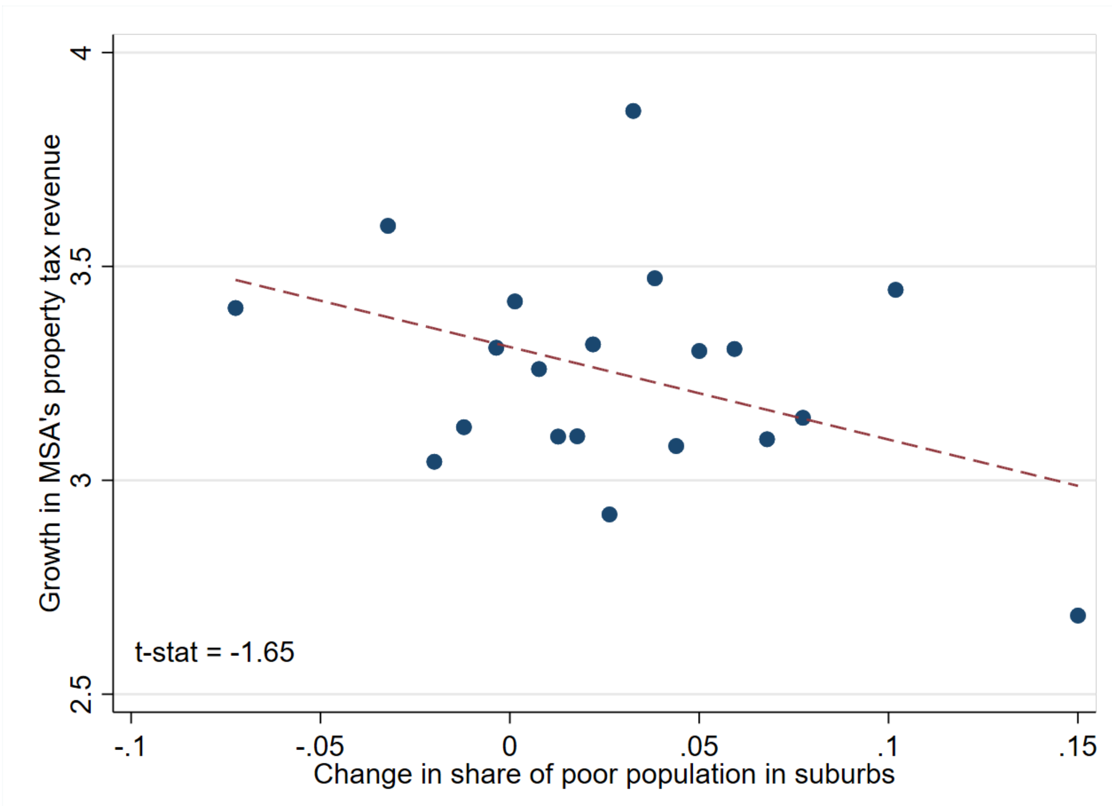
To examine these predictions empirically, we analyze the correlation between suburban poverty and property tax collections. We use Census data on municipal finances as provided by Williamette University (Pierson et al. 2015). We regress growth between 1992 and 2017 in property tax collections from suburban municipalities[23] of a given MSA on the change in the share of that MSA's poor population that lives in the suburbs. Controlling for the change in the share of the MSA's total population that lives in the suburbs, we find a

[23]We classify municipalities as urban, suburban, or rural by overlaying census tracts onto Census places.

statistically significant negative relationship (t=-3.5), displayed in Appendix Figure A.5. Suburban poverty decreases the ability of suburban municipalities to collect property taxes.

We repeat this analysis using property tax receipts for the MSA as a whole. In this regression, we control for the growth in the MSA's population[24]. We find that an increase in suburban poverty decreases growth in the MSA's total property tax receipts, though this effect is only marginally statistically significant at the 10% level. Nevertheless, this analysis suggests that changes in the geographical distribution of poverty may affect the overall amount of revenue collected from property taxes. Though we cannot claim that these relationships are causal, our evidence suggests that there is a relationship between the geographic distribution of poverty and aggregate property tax revenue.

Figure 10: Property tax revenue (MSA) and suburban poverty



Note: MSA-level binscatter. Depdendent variable is growth between 1992 and 2017 in the property tax revenue collected in an MSA. Independent variable is change in the share of that MSA's poor population that lives in the suburbs between 1990 and 2015-2019. Data for the change in suburban poverty comes from the 1990 decennial Census and 2015-2019 ACS. Data for municipal property tax revenue is from the Census of Governments, as provided by Willamette University.

[24]A similar analysis, using property tax receipts per capita instead of controlling for the growth in population finds similar results, though those results are marginally insignificant.

8.1.3 Public good quality

If tax revenue is spent efficiently on public goods, then the decrease in tax revenue documented above directly decreases the quality of local public goods. In this section we analyze how the quality of local schools responds to changes in suburban poverty, noting that declines in school quality may be especially costly for homeowners because it is more difficult for them to move in response to a change in public good quality[25].

To measure school quality, we use data from NCES on the high school completion rate of school districts[26] from 1991 through 1997. We obtain school district cohort graduation rates from 2015 through 2018 from the Department of Education's Ed Data Express. We aggregate suburban school districts together and compute the change in these measures of school completion over time for the suburban area of each MSA.

Regressing the change in school quality against the change in suburban poverty rates[27] at the MSA level in Appendix Figure A.6, we find that there is a statistically significant (t-stat = -2.13) negative relationship between these variables. Due to the presence of peer effects in education, a decline in school quality may effect residents throughout the school district. Though we do not claim that the relationship between suburban poverty and school quality is causal, a decline in the school and amenity quality in suburban areas due to an increase in poverty would decrease welfare.

8.2 Poverty creation

Though our mechanisms analysis indicates that Black suburbanization increases suburban poverty through sorting, we discussed in Section 2.2.2 that the suburbs have both created and attracted poverty since 1990. However, Black suburbanization cannot explain the entire increase in suburban poverty[28] nor the increase in poverty among incumbent suburban residents, which we do not believe is due to sorting. Our estimates from Appendix Table A.2 indicate that incumbent suburban poverty has, on net, increased by almost 1 million people since 1990.

Human capital externalities could explain some of the increase in poverty among incumbent suburban residents. As the suburbs have gotten poorer, average education levels in certain suburban neighborhoods have decreased. If the average education level of one's

[25] See Appendix A.3.4 for an alternative explanation.

[26] Unfortunately data for some large states, such as California, Texas and Michigan is not included in this dataset.

[27] We exclude observations with changes in their suburban poverty rate with absolute value greater than 0.1, which represent approximately the top and bottom 1% of values, from this analysis.

[28] Back of the envelope calculations in Section 5 imply that, at the MSA level, the increase in the Black share of the suburban population caused approximately $\frac{3}{4}$ of the increase in suburban poverty.

neighbors affect one's own income, then a decrease in average neighborhood education levels could increase poverty. For example, Moretti (2004) finds that a 1 percentage point increase in the college educated share causes a 1.9% increase in the income of low-skilled workers.

However, comparing the 1990 decennial Census with the 2015-2019 ACS, we find that fewer than 10% of suburban census tracts experienced a decline in their college educated share. Among those that did experience a decline, the median decrease was 2.8 percentage points. Using the estimate of human capital externalities above, a 2.8 percentage point drop in the college educated share could lead to a $2.8 * 1.9 = 5.3\%$ drop in income. Assuming that incomes right above the poverty line are distributed uniformly in these tracts, we calculate that 5.6% of those with incomes between one and two times the poverty line would be moved into poverty if income decreased by 5.3%[29]. In all, this decline in income would cause approximately 68,000 people to enter poverty. However, this analysis does not account for positive human capital externalities, which may have moved some suburban residents out of poverty due to the overall increase in suburban education levels.

Though human capital externalities cannot explain much of the increase in poverty among incumbent suburban residents, a decline in the quality of one's own educations or local public goods could affect residents' incomes. We showed in Appendix Figure A.6 that MSA-level school quality decreases as suburban poverty increases. However, we do not have direct estimates of the resulting effect on poverty. Further research should explore factors that have increased poverty among incumbent suburban residents in more depth.

8.3 Policy Responses

Though governments may be unable to stop individuals from segregating themselves on the basis of race and income, there are tangible policies local governments can take to ameliorate the effects of suburban poverty. Regional governments could start by addressing limited capacity in suburban anti-poverty programs, property tax shortfalls, and changing conditions in suburban schools. If school quality becomes less dependent on local poverty rates, residents may also be less likely to segregate themselves based on income.

Though Black suburban residents have been disproportionately exposed to the increase in suburban poverty, they need not be unduly exposed to low-quality suburban public goods. For example, local or regional governments could endeavor to reduce the impact that poverty has on communities by loosening the connection between local property values and school quality. A system with more centralized financing of local public goods may lessen the effect that poverty has on the amenities and welfare that suburban residents enjoy.

[29] $1.056 * (1 - .053) \approx 1$

9 Conclusion

In this paper, we explore whether the growing, predominantly middle-income, Black suburban population shifts the geographic distribution of poverty. While the suburbs have been seen as low-poverty areas since the middle of the 20$^{\text{th}}$ century, our model of residential choice demonstrates that poorer non-black individuals may follow Black residents into the suburbs, increasing suburban poverty and Black suburban residents' exposure to poverty.

Using a shift-share instrument, we find that suburban poverty, both overall and among the non-black population, increased as a result of Black suburbanization. We show that in suburbs that Black individuals entered, higher-income residents departed, bottom-quartile home prices declined, and lower-income individuals moved in. These results and key mechanisms hold between suburban areas within an MSA as well as between MSAs, and are robust to examining lagged outcomes. Our estimated coefficients imply that Black suburbanization can explain most of increase in suburban poverty observed in our data.

While millions of Black families moved to the suburbs to improve the quality of their living conditions, amenities, and neighborhoods, destination responses and an ongoing processes of neighborhood demographic change have increased their exposure to poverty. The suburbs are changing in ways that reduce the quality of neighborhoods in which Black families reside. Like Derenoncourt (2022) did for Black individuals growing up in destinations of the Great Migration, this paper has uncovered present-day limitations facing Black families seeking to move to opportunity.

Analyzing American suburbs in the 2015-2019 ACS indicates that the poverty rate of non-black residents in one's census tract is almost 1.5 times higher for the average non-poor Black suburban resident than for the average non-poor white suburban resident. Given that living in a lower-poverty neighborhood provides many benefits to children (Chetty et al. 2016), the unequal burden of suburban poverty may not only affect the welfare of suburban Black adults, but also their children.

Tackling suburban poverty will not only be beneficial for the suburban poor, but also for their communities. Although it is difficult for policymakers to address sorting and segregation, regional governments could increase revenue sharing to alleviate pressures on tax revenues and public good quality in poorer municipalities. Though many suburbs current lack effective anti-poverty programs (Allard 2017), there are existing poverty-reduction programs that can be implemented in the suburbs. However, since most research about these programs has been conducted in urban areas, we do not yet know how effective these approaches would be in the suburbs. Given the expansion of poverty into American suburbs and its myriad consequences, we believe this is a vital area for future research.

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A Appendix

A.1 Appendix Tables

Table A.1: Suburban poor population (millions)

Suburban Population (millions)		
Year	Poor and Black	Total Poor
1990	1.32	7.23
2015-2019	2.55	14.19

Notes: Data from 1990 decennial Census and 2015-2019 five-year ACS.

Table A.2: Suburban Poverty Creation and Attraction

Data source	Suburban poor	Change in suburban poor	Net poor in-migration to suburbs	Suburban poverty created
1990 Census	7.31		-.12	
2000 Census	8.76	1.45	.39	.67
2005 ACS	10.67	1.91	.17	1.08
2006 ACS	10.38	-.28	.21	-.49
2007 ACS	10.29	-.1	.13	-.23
2008 ACS	10.87	.58	.1	.49
2009 ACS	12.03	1.16	.12	1.04
2010 ACS	13.46	1.43	.09	1.33
2011 ACS	14.44	.98	.14	.84
2012 ACS	13.84	-.6	.02	-.62
2013 ACS	13.98	.14	.04	.1
2014 ACS	13.88	-.1	.04	-.14
2015 ACS	13.21	-.67	.1	-.77
2016 ACS	12.56	-.65	.09	-.74
2017 ACS	12.07	-.5	.11	-.6
2018 ACS	11.73	-.33	.01	-.34
2019 ACS	11.13	-.61	.02	-.63

Numbers in millions. Data from Census and ACS microdata. Methodology for calculating these figures explained in Sections 2.2.2 and A.3.3. The amount of suburban poverty created and net poor in-migration to suburbs is imputed for 1990, 2000 and 2005 using the methodology described in the text.

Table A.3: Demographic Changes in the Suburbs, 1990 to 2015-2019

	Mean	Std. Dev
Change in share of impoverished population in suburbs	0.046	0.053
Change in share of population in suburbs	0.036	0.044
Change in black share of suburban population	0.022	0.043

Note: Observations are at the MSA level, for 383 MSAs. Data from the 1990 decennial Census and 2015-2019 ACS.

Table A.4: Demographic mix in first equilibrium

r	City	Suburb 1	Suburb 2
w	250	250	250
b	250	0	0

Note: Numbers from model simulation.

Table A.5: Demographic mix in second equilibrium

r	City	Suburb 1	Suburb 2
w	27	163	560
b	71	179	0

Note: Numbers from model simulation.

Table A.6: Shift-share example: Black migration to Boston and Cleveland

Boston			
County	City	Share s_{ik}	Shock g_k
Norfolk City, VA	Norfolk	0.025	-182
New Hanover, NC	Wilmington	0.020	641
Richmond, GA	Augusta	0.018	156
$z_i = \sum_k s_{ik} g_k$			11.1
Increase in suburban black share			0.032

Cleveland			
County	City	Share s_{ik}	Shock g_k
Jefferson, AL	Birmingham	0.060	683
Fulton, GA	Atlanta	0.040	-315
Shelby, TN	Memphis	0.034	41.7
$z_i = \sum_k s_{ik} g_k$			29.8
Increase in suburban black share			0.050

Notes: The above table displays data on Black migration during the Great Migration. Data for the shares comes from the 1940 full-count Census, and represents the share of all Black migrants to the given city who lived in the specified county in 1935. The shocks are the percent growth in the amount of Black net out-migration from the given county between 1940 and 1970, using data from Boustan (2016). The increase in the suburban Black share is measured between the 1990 decennial Census and 2015-2019 ACS.

Table A.7: Robustness: Pre-trends test

	Change in suburban poverty 1980-1990		
	(1)	(2)	(3)
Change in suburban Black share	-0.362**	-0.604*	0.862
	(0.171)	(0.343)	(0.590)
Observations	1174	1174	1174
Control Variables	No	Yes	Yes
Population Weighting	No	No	Yes
Effective F-statistic for IV	12.9	16.6	8.4

Note: Exposure robust standard errors are clustered at the shock (Southern county) level. The dependent variable is the change in the share of the poor population of the MSA that lives in the suburbs. The independent variable is the change in the suburban Black share between 1990 and 2015. Control variables at the MSA level are total population in 1990 and Census Region fixed effects. Regressions weights in column three are based on MSA population in 1990. In this table, we set $e_i = 1$ and use the instrument that does not account for distance to the suburbs. *** indicates significance at the 1% level.

Table A.8: Robustness: Without suburban distance weights

	Change in suburban poverty			Change in non-black suburban poverty		
	(1)	(2)	(3)	(4)	(5)	(6)
Change in suburban Black share	2.329***	3.371***	6.980***	1.629***	2.311***	4.957***
	(0.355)	(0.612)	(1.835)	(0.313)	(0.594)	(1.589)
Observations	1174	1174	1174	1174	1174	1174
Control Variables	No	Yes	Yes	No	Yes	Yes
Suburban Distance Weighting	No	No	No	No	No	No
Population Weighting	No	No	Yes	No	No	Yes
Effective F-statistic for IV	12.9	16.6	8.4	11.6	14.6	5.5

Note: Exposure-robust standard errors are clustered at the shock (Southern county) level. Dependent variables are the change between 1990 and 2015-2019 in the share of the poor population, or in the share of the poor non-black population, of the MSA that lives in the suburbs. The independent variable is the change in the suburban Black share between 1990 and 2015. Control variables at the MSA level are total population in 1990 and Census Region fixed effects. Regressions weights in columns three and six are based on MSA population in 1990. In this table, we set $e_i = 1$ and use the instrument that does not account for distance to the suburbs. *** indicates significance at the 1% level.

Table A.9: Black suburbanization and black suburban poverty: Clustered standard errors

	Change in suburban poverty		
	(1)	(2)	(3)
Change in suburban Black share	1.795***	2.345***	3.657**
	(0.386)	(0.646)	(1.730)
Observations	1174	1174	1174
Control Variables	No	Yes	Yes
Suburban Distance Weighting	Yes	Yes	Yes
Level of SE cluster	State	State	State
Population Weighting	No	No	Yes
Effective F-statistic for IV	4.5	6.7	2.2

Note: Exposure robust standard errors are clustered at the state level. The dependent variable is the change in the share of the poor population of the MSA that lives in the suburbs. The independent variable is the change in the suburban Black share between 1990 and 2015. Control variables at the MSA level are total population in 1990 and Census Region fixed effects. Regressions weights in column three are based on MSA population in 1990. *** indicates significance at the 1% level.

Table A.10: Black suburbanization and non-black suburban poverty: Clustered standard errors

	Change in non-black suburban poverty		
	(1)	(2)	(3)
Change in suburban Black share	0.982***	1.285***	1.731
	(0.268)	(0.493)	(1.397)
Observations	1174	1174	1174
Control Variables	No	Yes	Yes
Suburban Distance Weighting	Yes	Yes	Yes
Level of SE cluster	State	State	State
Population Weighting	No	No	Yes
Effective F-statistic for IV	4.6	6.8	1.7

Note: Exposure robust standard errors are clustered at the state level. The dependent variable is the change in the share of the poor non-black population of the MSA that lives in the suburbs. The independent variable is the change in the suburban Black share between 1990 and 2015. Control variables at the MSA level are total population in 1990 and Census Region fixed effects. Regressions weights in column three are based on MSA population in 1990. *** indicates significance at the 1% level.

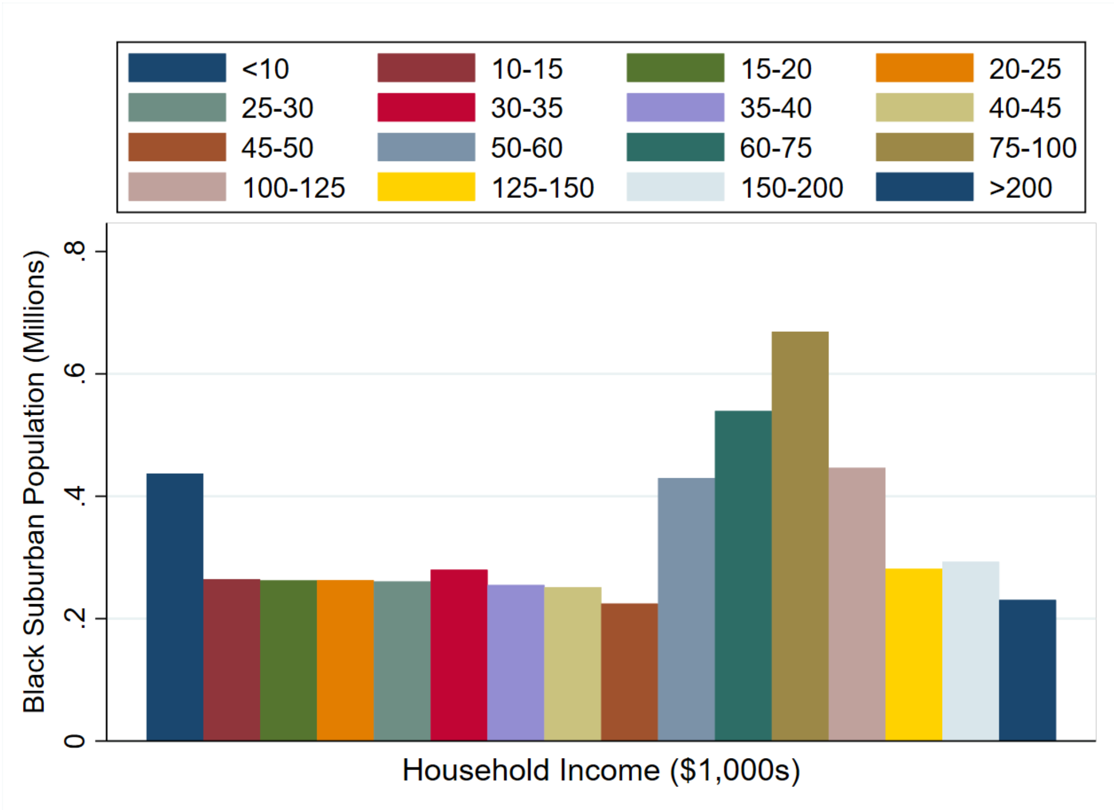
Table A.11: Robustness: Between MSA changes in poverty (timing)

	Change in suburban poverty			Change in non-black suburban poverty		
	(1)	(2)	(3)	(4)	(5)	(6)
Change in suburban Black share 1990-2000	2.755***	3.402***	3.215***	1.516***	2.208***	1.465
	(0.549)	(0.798)	(0.768)	(0.539)	(0.779)	(0.894)
Observations	1174	1174	1174	1174	1174	1174
Control Variables	No	Yes	Yes	No	Yes	Yes
Suburban Distance Weighting	Yes	Yes	Yes	Yes	Yes	Yes
Population Weighting	No	No	Yes	No	No	Yes
Effective F-statistic for IV	18.2	17.2	10.0	17.5	16.9	7.3

Note: Exposure robust standard errors are clustered at the shock (Southern county) level. Dependent variables is the change between 2000 and 2015-2019 in the share of the poor population, or of the poor non-black population, of the MSA that lives in the suburbs. The independent variable is the change in the suburban Black share between 1990 and 2000. Control variables at the MSA level are total population in 1990 and Census Region fixed effects. Regressions weights in columns three and six are based on MSA population in 1990. *** indicates significance at the 1% level.

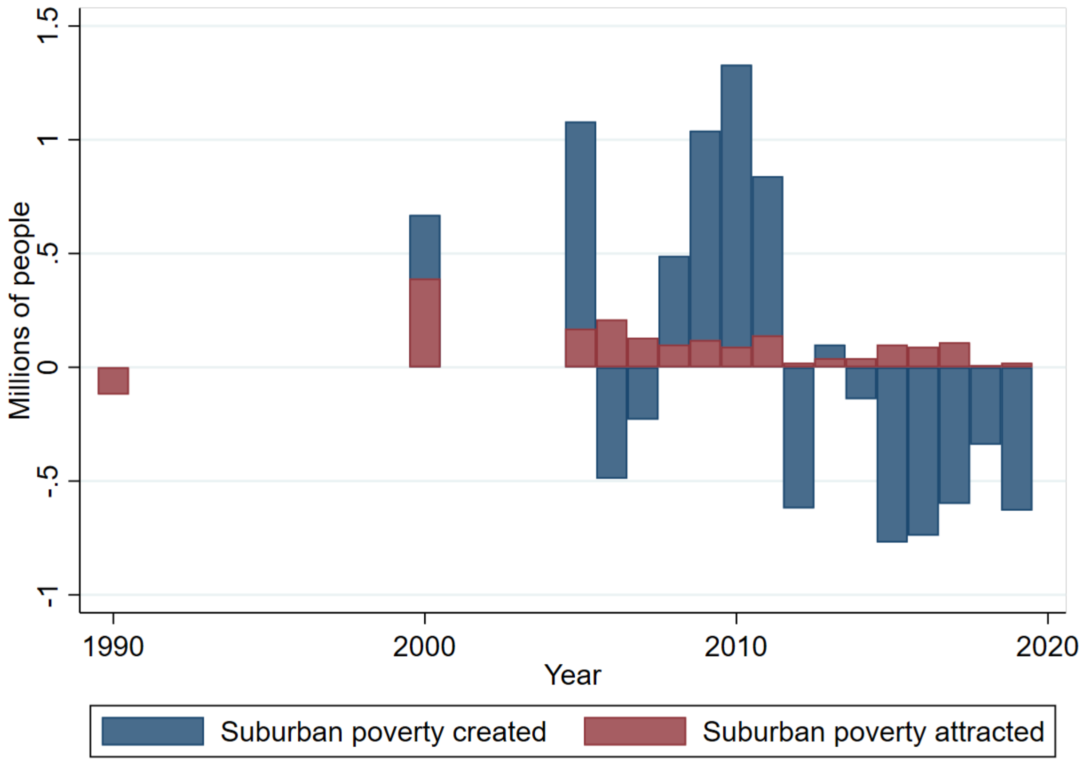
A.2 Appendix Figures

Figure A.1: Annual income among suburban Black households, 2015-2019 ACS



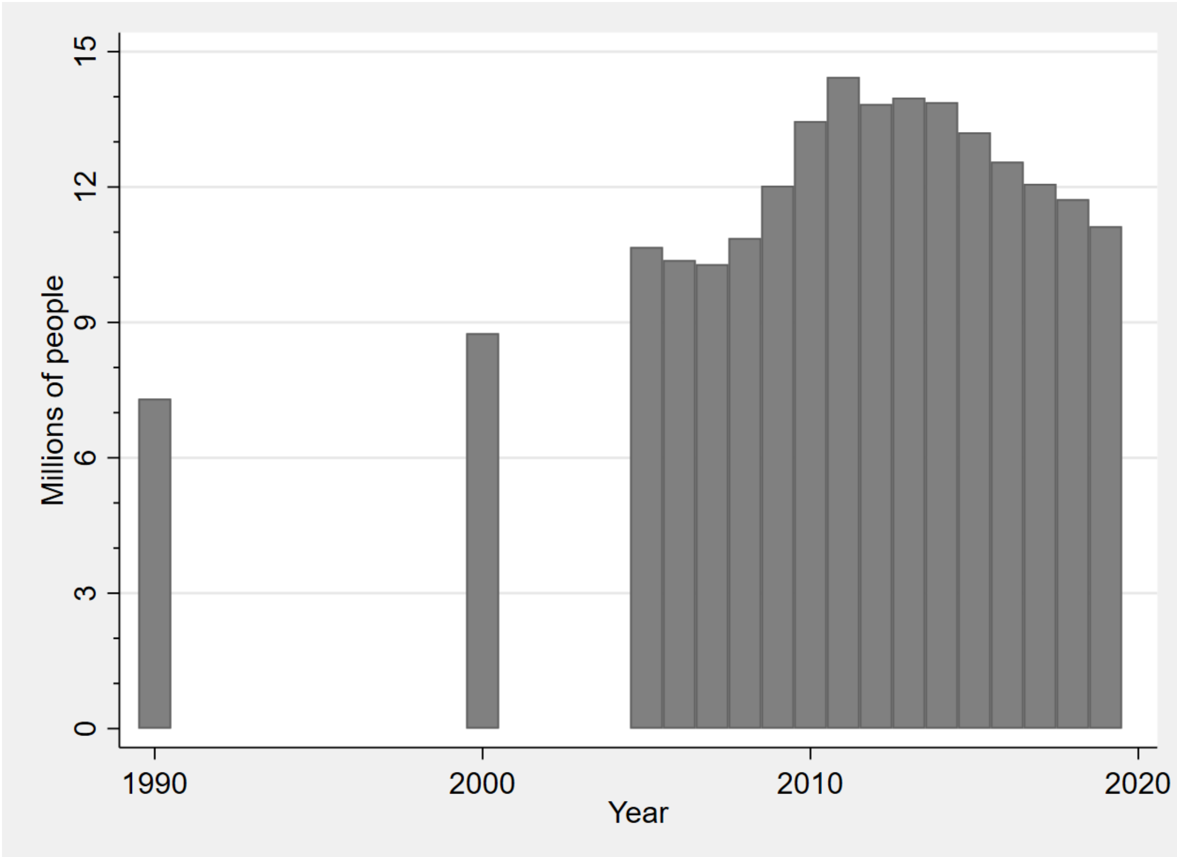
Note: Household income data for Black families aggregated for all suburban census tracts in the 2015-2019 five-year ACS.

Figure A.2: Suburban Poverty Creation and Attraction



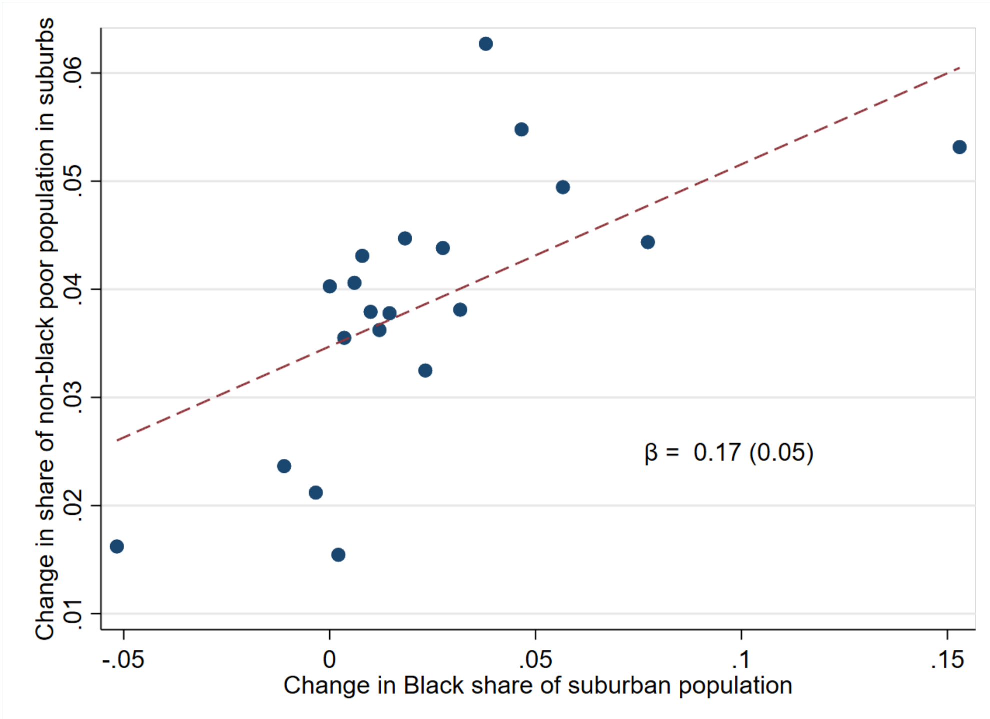
Note: Microdata from the decennial Census (1990 and 2000) and one-year ACS files (2005-2019). We calculate poverty creation as the change in the number of individuals under the poverty line between t and $t-1$ among those who were in the suburbs in year t, and poverty attraction as the net migration into the suburbs of impoverished individuals between periods. These calculations are described in more detail in Sections 2.2.2 and A.3.3.

Figure A.3: Suburban Poor Population



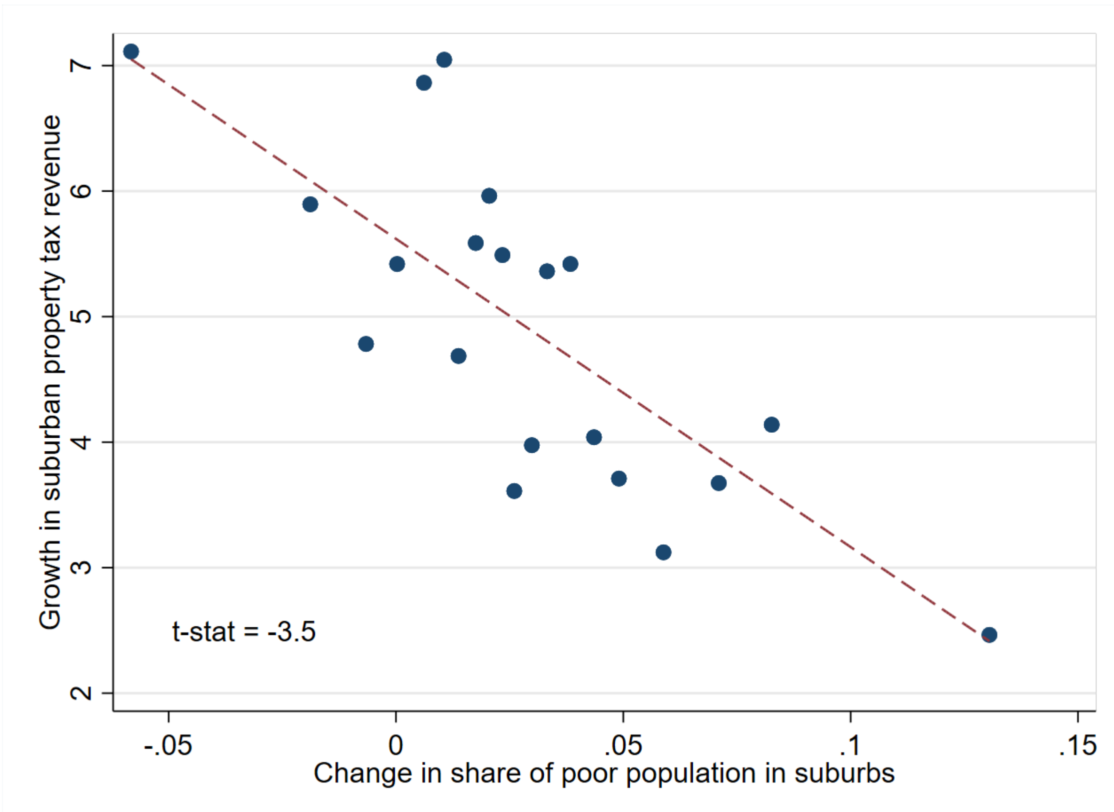
Note: This figure counts the number of impoverished individuals currently living in the suburbs, using data from Census and ACS microdata.

Figure A.4: Black suburbanization and non-black suburban poverty



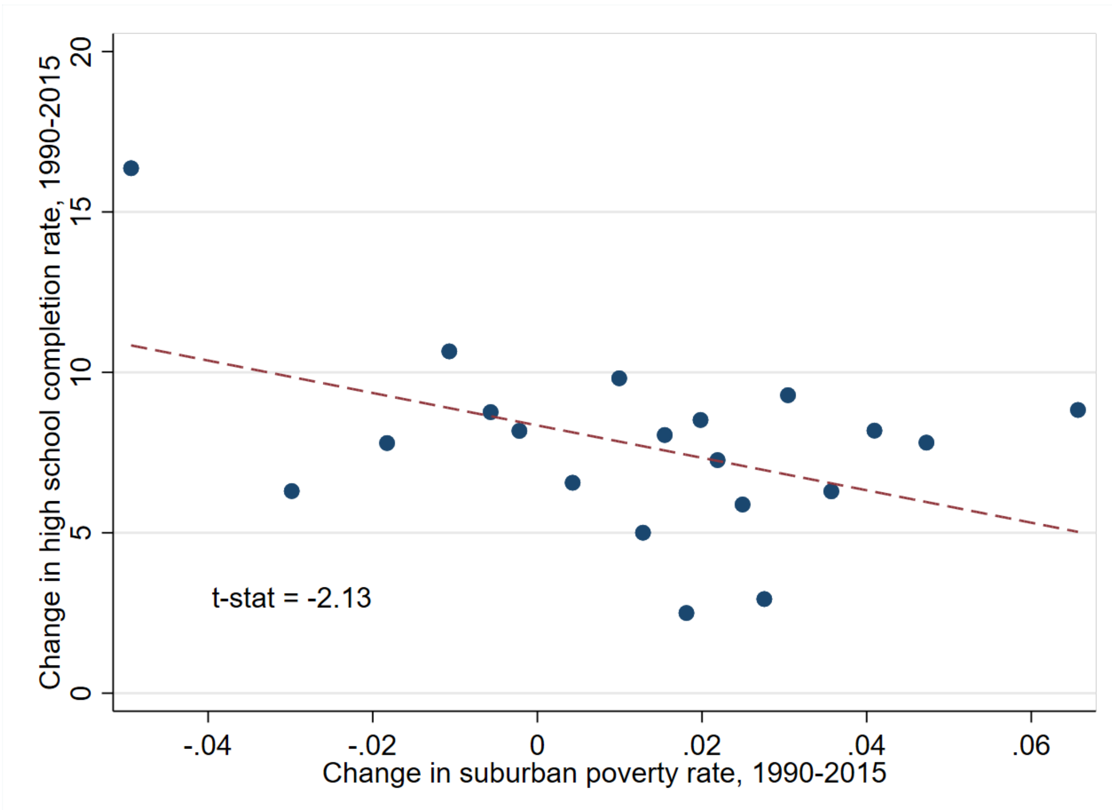
Note: MSA-level binscatter of the change in the share of the non-black poor population that lives in the suburbs on the change in the share of the suburban population that is Black, controlling for the change in the share of the non-black MSA population that is suburban. All variables are measured as changes between the 1990 decennial Census and 2015-2019 five-year ACS. There are 364 MSAs represented in the binscatter.

Figure A.5: Suburban property tax revenue and suburban poverty



MSA-level binscatter of the relationship between the growth between 1992 and 2017 in the property tax revenue collected in the suburbs of the MSA and the change in the share of the MSA's poor population that lives in the suburbs between 1990 and 2015-2019. Data for the change in suburban poverty comes from the 1990 decennial Census and 2015-2019 ACS. Data for property tax revenue is from the Census of Governments, as provided by Willamette University.

Figure A.6: School quality and suburban poverty



Note: MSA-level binscatter of the change in graduation rates (measured as the high school completion rate between 1991 and 1997, and district cohort graduation rates between 2015 and 2018) for the suburban area of each MSA against the change in that MSA's suburban poverty rate between the 1990 decennial Census and 2015-2019 ACS. We exclude observations with an absolute value of the change in the suburban poverty rate above 0.1.

A.3 Appendix Materials

A.3.1 Shock-level Regression

The weighted shares and residuals for Southern county k are defined, respectively, below, where regression weights e_i and residuals ε_i come from the MSA-level equation 2:

$$s_k = \sum_i e_i \, s_{ik}, \; \tilde{\varepsilon}_k = \frac{\sum_i e_i s_{ik} \varepsilon_i}{\sum_i e_i s_{ik}} \tag{14}$$

The Stata program *ssaggregate* residualizes $\Delta_{1990,2015}\, x_i$ and $\Delta_{1990,2015}\, y_i$ from MSA-level equation 2 on the vector of control variables using regression weights e_i. This gives us the residualized variables $y_i^{\perp}$ and $x_i^{\perp}$. These residualized variables are then converted to the shock level (where they are used in the regressions) by taking an exposure-weighted average:

$$\bar{y}_k^{\perp} = \frac{\sum_i e_i s_{ik} y_i^{\perp}}{\sum_i e_i s_{ik}} \, , \bar{x}_k^{\perp} = \frac{\sum_i e_i s_{ik} x_i^{\perp}}{\sum_i e_i s_{ik}} \tag{15}$$

A.3.2 Ray Construction

The directional ray for each MSA is constructed using the first (or second) principal city that has an identifiable place point in 1960[30]. We use these place points as a proxy for the city's central business district (CBD).

Once we have our restricted sample of viable MSAs, we loop through each city-MSA pair to construct Black neighborhoods. Using 1960 census data on race and population at the tract level, we use GIS data to split the city into four directional quadrants, centered at the CBD. We then calculate the share of the city's 1960 Black population in each quadrant. If one quadrant contains 75% or more of the city's Black population, we decide to construct one predominant Black neighborhood in that city. Otherwise, we construct two to capture the possibility of two distinct, separated neighborhoods in different quadrants. In both cases, we utilize an iterative process to choose the sample of tracts that will be used in constructing either one or two neighborhoods. Tracts are chosen based on their Black population share, and the total coverage of the city's Black population share within that tract group. We start our threshold for Black population share at 30%, select the tracts that are greater than or equal to that threshold, then check how much of the Black population is accounted for in that group. If the tract group covers 75% of the city's Black population, we proceed. If it does not, we decrease the threshold by 5% and continue.

[30] In instances where the first prinicpal city does not have an identifiable place point, we try to use the second principal city.

Once we have a set of tracts that constitute the Black neighborhood(s), we can then construct weighted-population centroids. In the case of one neighborhood, we take the tract group as given and construct the weighted-centroid, weighting the latitude and longitude of the centroid of each tract t in MSA m with the tract's 1960 Black population p_{tm}. The population-weighted centroid is like any other weighted average:

$$Centroid_m = \left(\frac{\sum_{t=1}^{T} p_{tm} Lat_{tm}}{\sum_{t=1}^{T} p_{tm}}, \frac{\sum_{t=1}^{T} p_{tm} Long_{tm}}{\sum_{t=1}^{T} p_{tm}} \right) \tag{16}$$

In the case of two neighborhoods, we rely on a k-means clustering algorithm. The algorithm clusters data by separating our sample of tracts into two groups of equal variance, minimizing a criterion known as the "inertia" or within-cluster sum-of-squares. In practice, we feed the algorithm the latitude and longitude of our selected sample of tract centroids, and it returns cluster identifiers for each tract in the sample. Within these defined clusters, we then proceed to construct our Black-population-weighted-centroids as above in Equation 16.

With both the CBD and Black neighborhood centers defined, we then create the rays starting at the CBD, passing through the neighborhood center(s), and extending through the 2019 city boundary shapes.

A.3.3 Poverty decomposition

To calculate the number of people moving into and out of the suburbs, we need data from consecutive time periods. For 1990, 2000, and 2005, our migration data does not span the entire time period, so we instead assume that unobserved migration flows (those in the earlier part of the decade) are equal to observed migration flows (those in the later part of the decade)[31].

To examine transitions into and out of suburban poverty, we group people according to their poverty status, poor ($p = 1$) or not poor ($p = 0$), and their location, suburban ($s = 1$) or not suburban ($s = 0$), in time periods $t - 1$ and t. There are three possible ways to enter suburban poverty at time t:

Transitions into suburban poverty		
Status in $t-1$	$s_{t-1} = 0$	$s_{t-1} = 1$
$p_{t-1} = 0$	A	B
$p_{t-1} = 1$	C	D

[31] For example, we assume that the net movement of the poor population into the suburbs between 1990 and 1995, which we cannot observe in the data, is the same as the net movement of the poor population into the suburbs between 1995 and 2000, which we can observe in the data.

In time period $t-1$, members of group A were not poor and lived outside the suburbs while members of group B were not poor and lived in the suburbs. Members of group C were poor, but lived outside the suburbs. Group D was already in suburban poverty.
There are also three ways one can transition from being in suburban poverty at time $t-1$ to no longer being in suburban poverty at time t:

Transitions out of suburban poverty		
Status in t	$s_t = 0$	$s_t = 1$
$p_t = 0$	E	F
$p_t = 1$	G	H

Members of groups E and F left poverty, and now live outside and within the suburbs, respectively, while members of group G remained in poverty but moved out of the suburbs. Group H remains in suburban poverty.
There is one more relevant group, which we will call group J. Members of group J were not poor when they lived in the suburbs but became poor when they moved out of the suburbs. That is, for members of group J $s_{t-1} = 1, p_{t-1} = 0, s_t = 0,$ and $p_t = 1$.
To examine whether the increase in suburban poverty is mainly caused by poorer people moving into the suburbs or incumbent suburban residents becoming poorer, we aggregate the above groups into two categories.
The first category is "suburban poverty attraction", which we define as the net movement of poor individuals into the suburbs. This is the number of individuals who moved into the suburbs and are poor in period t (members of groups A and C) minus the number of individuals who moved out of the suburbs while poor in period t (members of groups G and J).
The second category is "suburban poverty creation", which we define as the difference between the number of people who were in the suburbs in $t-1$ and entered poverty in period t (members of groups B and J) compared with those who were in the suburbs in $t-1$ and left poverty in period t (members of groups E and F).
Letting each letter now represent the number of people in each group, we have:

$$\begin{aligned}&\text{Suburban poverty attraction} + \text{Suburban poverty creation} = \\ &(A + C - G - J) + (B + J - E - F) = \\ &A + B + C - E - F - G = \\ &\text{Change in number of suburban poor}\end{aligned} \tag{17}$$

We use the microdata described in Section 2.2.2 to quantify the amount of poverty creation and attraction. The microdata does not follow individuals over time, so we cannot calculate the number of individuals in each individual group described above.

A.3.4 Effect of home prices on homeowners

Many spatial models take the following form, such as in Couture, Gaubert, et al. (2024):

$$V_{ij} = (Y_i - p_j)B_j\epsilon_{ij} \tag{18}$$

Here, V_{ij} is household i's indirect utility for living in area j, B_j measures the quality of amenities in area j and ϵ_{ij} is household i's idiosyncratic preference for living in area j. As in our model, Y_i is the income of household i and p_j is the price of housing in area j.
It is clear that in this utility function, $\frac{\partial V}{\partial p_j} < 0$ and $\frac{\partial V}{\partial B_j} > 0$. That is, household benefit from decreases in prices of housing and increases in public good quality.
However, we argue that the utility of those who already own a home should resemble:

$$V'_{ij} = (Y_i + \kappa p_j)B_j\epsilon_{ij} \tag{19}$$

Note that for someone who owns a home in j, changes in p_j do not affect their payment for housing[32], while increases in p_j increase the value of their home equity. Additionally, if public goods are financed from local property taxes, $\frac{\partial B_j}{\partial p_j} > 0$. Therefore, we argue that $\frac{dV'}{\partial p_j} > 0$ for homeowners. That is, their utility will decline if an increase in poverty depresses housing prices, and this decline is larger than for renters because $\frac{dV'}{\partial p_j} > \frac{dV}{\partial p_j}$.

[32]Housing costs could rise if property taxes increase due to a rise in their home's assessment value. In this case, the effects on utility from the additional property tax payment and increase in public good quality may cancel each other out, but the homeowner still benefits from the increased value of their equity.