Race, Poverty, and the Changing American Suburbs

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Abstract

We study how the socioeconomic composition of the suburbs changes in response to Black suburbanization. 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 and the distance from urban Black neighborhoods to the suburbs. Our results at the metropolitan-area level indicate that rich and college-educated non-Black residents become less likely to live in the suburbs, while impoverished (non-Black) residents become more likely to live in the suburbs, as a result of Black suburbanization. We find evidence of a process of neighborhood change in which suburban home prices fall as Black families move in, inducing lower-income residents to move into the suburbs and disproportionately increasing Black suburban residents' exposure to poverty. Using a new instrument to analyze these mechanisms within metropolitan areas yields similar results. Our findings provide another example of how destination responses impede Black Americans' ability to move to opportunity.

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1 Introduction

The American suburbs are changing. The Black suburban population doubled between 1990 and 2019, primarily due to middle-income Black families moving to the suburbs in search of better neighborhoods (Bartik and Mast 2023). However, American history is replete with examples of White families moving away from their new Black neighbors (Shertzer and Walsh (2019), Rothstein (2017), Boustan (2010)). Studies have found mixed evidence for "White flight" in the suburbs[1], but they have found descriptive evidence of a new pattern: higher-income White suburban residents are more likely to move after Black families arrive than are lower-income White suburban residents (Kye (2018), Parisi et al. (2019)).

At the same time that richer suburban residents are moving, suburban poverty is increasing (Kneebone and Garr (2010), Allard (2017)). The relationship between Black suburbanization and these changes in the suburban income distribution has not been causally investigated. If richer residents leave the suburbs and poorer residents enter the suburbs due to the arrival of Black residents, then the Black families that moved to the suburbs in search of better neighborhoods may instead find that the suburbs are changing around them.

This paper studies the relationship between Black suburbanization and the changing socioeconomic composition of the suburbs. We begin by developing a simple model of residential choice that demonstrates how suburban poverty can increase when richer residents leave suburban neighborhoods that middle-income 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 live in one suburban area, while richer White residents live in a different suburban area. This equilibrium exists because richer Black residents are willing to pay to live in more diverse communities, while richer White residents pay to live in more expensive, racially homogeneous neighborhoods. However, the model does not predict how much the suburban income distribution will change for a given increase in the Black suburban population. We estimate this relationship empirically.

We develop a novel shift-share instrument for the changing racial composition of Northern suburbs to analyze how the socioeconomic composition of the suburbs changes in response to Black suburbanization. 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 of 1940 to 1970 with pre-existing migrant networks (shares) that linked Southern counties to Northern cities.[2] We add a new source of variation by incorporating the distance

[1] Compare, for example, Bartik and Mast (2023) with Kye (2018).

[2] We follow the classification of Southern states from Boustan (2010). "Northern" refers to all areas in the United States outside of these Southern states.

between the 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 changes in the income distribution of Northern suburbs from 1990 to 2019.[3] For example, if one worries that Black families chose to move to suburban areas that were already becoming less wealthy, our instrument addresses this issue so long as shocks to Black out-migration from the South during the Great Migration are not related to omitted correlates of these present-day trends in the Northern suburbs.

Using this instrument to analyze data from the 1990 decennial census and 2015–2019 American Community Survey (ACS), we find that wealthier and better-educated non-Black residents become less likely to live in suburban areas that Black residents enter, while poorer (non-Black) residents become more likely to live in these suburbs. We find that the share of the rich non-Black metropolitan-area population that lives in the suburbs decreases by approximately one percentage point in response to a one percentage point increase in the Black share of the suburban population. Black suburbanization also precipitates an increase in the proportion of poor non-Black residents that live in the suburbs. These findings imply that the increase in suburban poverty disproportionately affects Black suburban residents.

We find evidence that a process of neighborhood change, sparked by the response of incumbent residents to Black suburbanization, drives our results. Using our instrument for Black suburbanization, we find that growth in the Black suburban population depresses growth in bottom-quartile suburban home prices. Using Census microdata to analyze the migration of lower-income residents, we find a strong correlation between Black movement into suburban areas and the subsequent movement of lower-income residents into those areas.

We use spatial patterns of Black suburbanization to construct a new instrument to analyze changes within metropolitan areas. This instrument for Black suburbanization within a metropolitan area is based on patterns in the direction in which Black individuals migrated away from the city center. Specifically, Black population growth varies among suburban areas in a given metropolitan area based on how far the area is from the predicted vector of Black suburbanization. Our results for this within-metropolitan-area analysis are consistent with our overall results, as we find declines in home prices and increases in non-Black poverty in areas with more Black suburbanization.

While we show that the increase in suburban poverty disproportionately affects Black

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

suburban residents, this paper does not assess the overall welfare effect of moving to the suburbs. As Bartik and Mast (2023) note, Black movement to the suburbs has led to large increases in average neighborhood quality for Black individuals. The changes in the suburban environment arising from responses to Black in-migration should therefore be placed in this context: neighborhood quality and amenities improve, on average, when moving to the suburbs. However, we argue that neighborhood quality and amenities for Black families would have improved *more* had wealthier suburban residents not sparked a process of neighborhood change by leaving the suburbs in response to Black families moving in.

Additionally, while our analysis indicates that Black suburbanization is primarily related to changes in the suburban income distribution through sorting, we also 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. Although we do not quantify its impact, changes in public good provision may also contribute to the increase in the incumbent poor population. We find that overall property tax collections and school quality decrease in suburbs that are becoming poorer, which may further increase suburban poverty among incumbent residents. 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), Shertzer and Walsh (2019), Akbar et al. (2022) and others. Shertzer and Walsh (2019) and Boustan (2010) document how White residents fled as Black migrants entered Northern cities (between 1900 and 1930, and 1940 and 1970, respectively), while Card et al. (2008) describes nonlinearities in incumbent responses to racial change between 1970 and 2000. We build on these papers by studying responses to racial change in present-day American suburbs, and by documenting changes in the economic composition of the suburbs in addition to changes in racial composition.

Furthermore, 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, although these papers document incumbent flight, they do not address the subsequent in-movement of the poor population, which we track using public Census microdata. We document the longer-term series of events that accompanies Black migration to the suburbs: richer and better-educated incumbent residents leave, property prices fall, and poorer residents move in.

Second, this paper provides further evidence that the general equilibrium effects of large-scale "movement to opportunity" among the Black population are smaller than those of individual moves (such as in Chetty et al. (2016), Chyn (2018), Chyn, Collinson, et al. (2023) and Haltiwanger et al. (2024)). For example, 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 that offered Black children improved opportunities in the 1940s no longer do so. Akbar et al. (2022) documents how inflated rental prices and deflated home values in Black neighborhoods of Northern cities during the Great Migration diminished the economic gains that migrating Black individuals could accrue.

We document a similar pattern while studying the subsequent, and currently ongoing, wave of Black migration to the suburbs. Neighborhood change in the suburbs, which increases Black suburban residents' exposure to poverty, may be an important mechanism reducing the gains from moving to the North that Derenoncourt (2022) finds Black residents experience. Suburban poverty is therefore another example of how, for at least the better part of a century, destination reactions have made it harder for Black Americans to move to opportunity.

Finally, this paper enriches our understanding of the spatial distribution of income within metropolitan areas. Although we investigate different mechanisms, our novel empirical evidence supports the theoretical predictions of "the poor mov(ing) to the suburbs" from as early as LeRoy and Sonstelie (1983). More recent 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 departure of wealthier non-Black individuals and the arrival of poorer non-Black individuals as a result of Black suburbanization. These papers, considered together with the present work, allow us to better understand how the spatial distribution of income is changing throughout metropolitan areas.

2 Black Suburbanization and the Suburban Income Distribution: Data and Description

In this section, we describe the data we need to determine the relationship between Black suburbanization and the socioeconomic composition of the suburbs. We use these data to provide an overview of national trends in Black suburbanization and a noticeable shift in the suburban income distribution towards increased 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)[4]. We obtain data on suburban racial composition from the decennial census (1990) and five-year American Community Survey (ACS, 2015–2019)[5]. We measure the total population and the Black non-Hispanic population in each suburban census tract.

Using these 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.

2.2 Suburban Wealth, Education and Poverty

In this section, we describe how we measure suburban wealth, education levels, and poverty. In the latter two subsections we describe the increase in poverty, which represents the most pronounced change in the suburban income distribution in recent decades. We show how, although starting from a low level, suburban poverty has increased concurrently with Black suburbanization. We decompose the increase in poverty into contributions coming from movers versus from stayers to help elucidate causes of the increase.

[4]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), although 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.

[5]We obtain these tract-level data with constant 2010-tract boundaries from Social Explorer (Social Explorer 2024).

2.2.1 Data

We obtain data on the socioeconomic composition of the suburbs from the decennial census (1990) and five-year ACS (2015–2019) through Social Explorer (Social Explorer 2024). We count the number of households with income above $25,000 in constant 1980 dollars in each census tract, whom we refer to as "rich".[6] We obtain data on educational attainment from these sources as well, and count the number of people with at least a college (B.A.) degree in each census tract. Finally, we count the number of people who are in households that are in poverty in each census tract. 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.

2.2.2 Quantifying the increase in suburban poverty

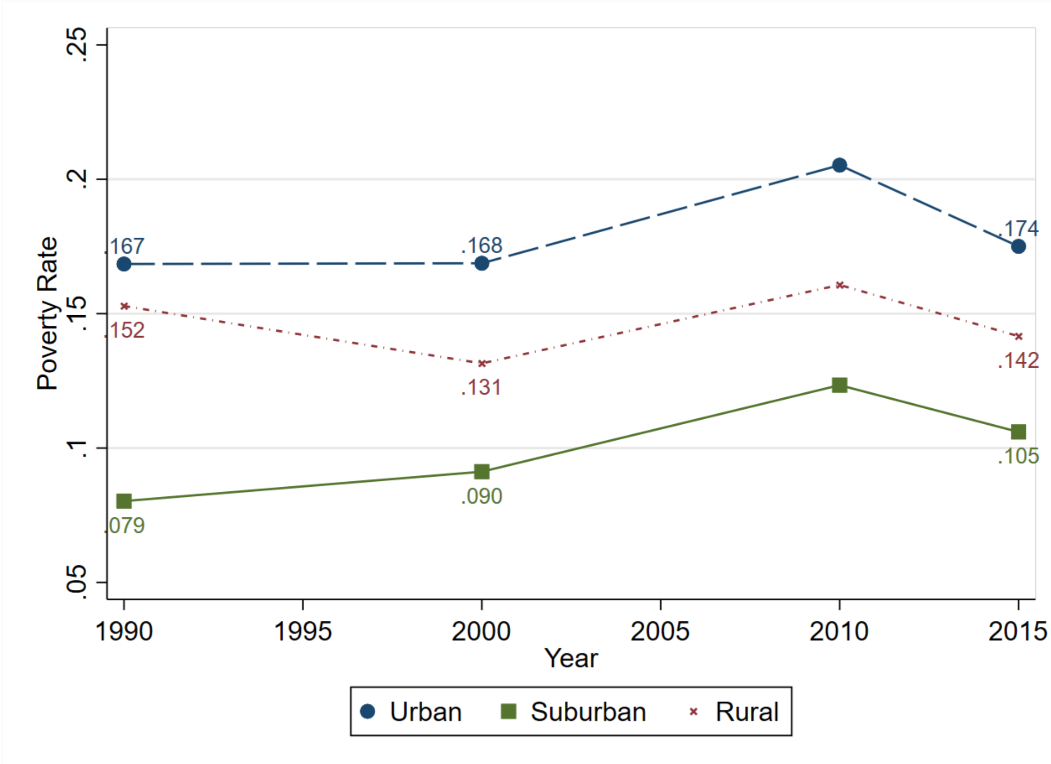
We next focus on the change in suburban poverty and quantify its increase in two ways. First, we show that the poverty rate in the suburbs has increased, both absolutely and relative to urban and rural areas. Second, we show that the share of impoverished Americans who live in the suburbs has risen. These broad trends have previously been identified[7] but have not been discussed at length in the economics literature.

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.

[6]We use 1980 dollars because our pretrend analysis begins in 1980. $25,000 in 1980 dollars is equivalent to $95,622 in September 2024. Our results are robust to a variety of definitions of "rich".

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

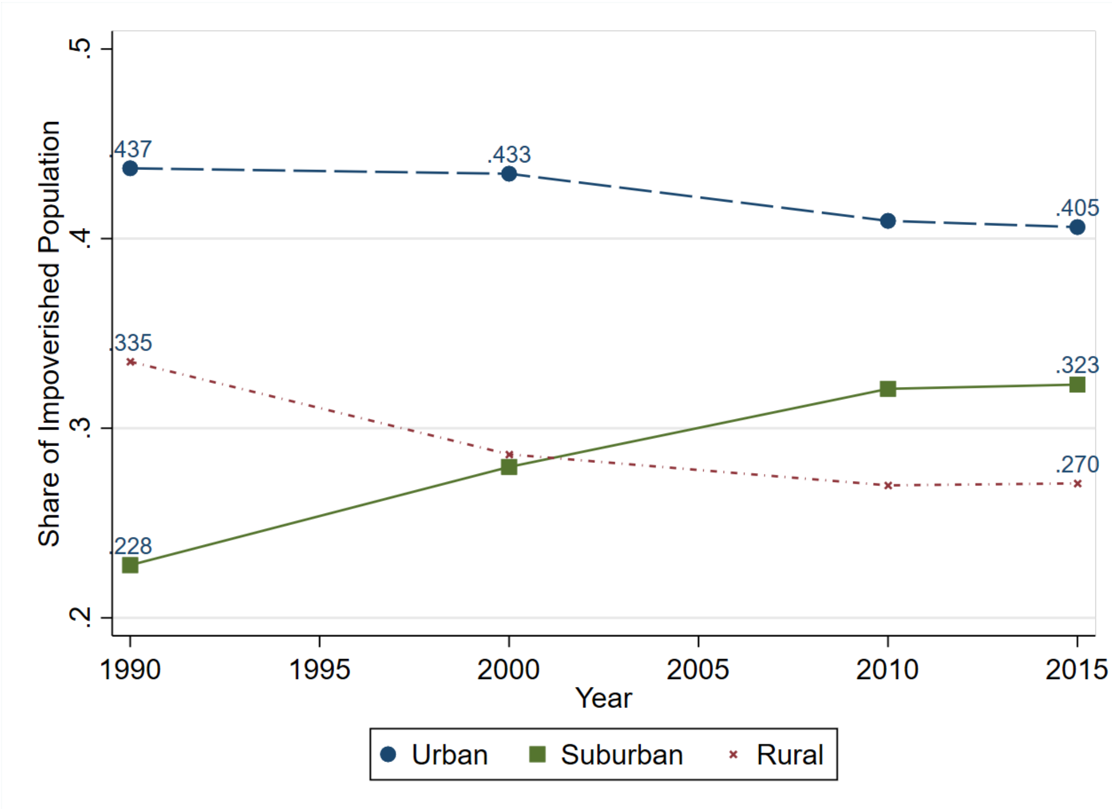
Figure 1: Poverty rates



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 increased by 9.5 percentage points during this time, while the percentage of all Americans who live in the suburbs increased by only 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.

2.2.3 Decomposing the increase in suburban poverty

Although we know that the suburbs became poorer at the same time that Black residents moved in, we want to determine whether this 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[8] and poverty creation as the change in the number of individuals

[8]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 24. 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. Further details on our calculations are available in Appendix A.3.4.

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 greater detail in Appendix Table A.1, indicate that the suburbs created poverty even during the period of relatively favorable economic conditions between 1990 and 2005[9]. 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.

2.3 Black Suburbanization and Changes in Suburban Income

While both the Black and impoverished suburban populations grew at the national level between 1990 and 2015–2019, these increases could have occurred in different metropolitan areas. However, we find that suburban poverty increased in the same MSAs that experienced greater amounts of Black suburbanization. Additionally, the share of rich non-Black residents living in the suburbs fell in these same MSAs.

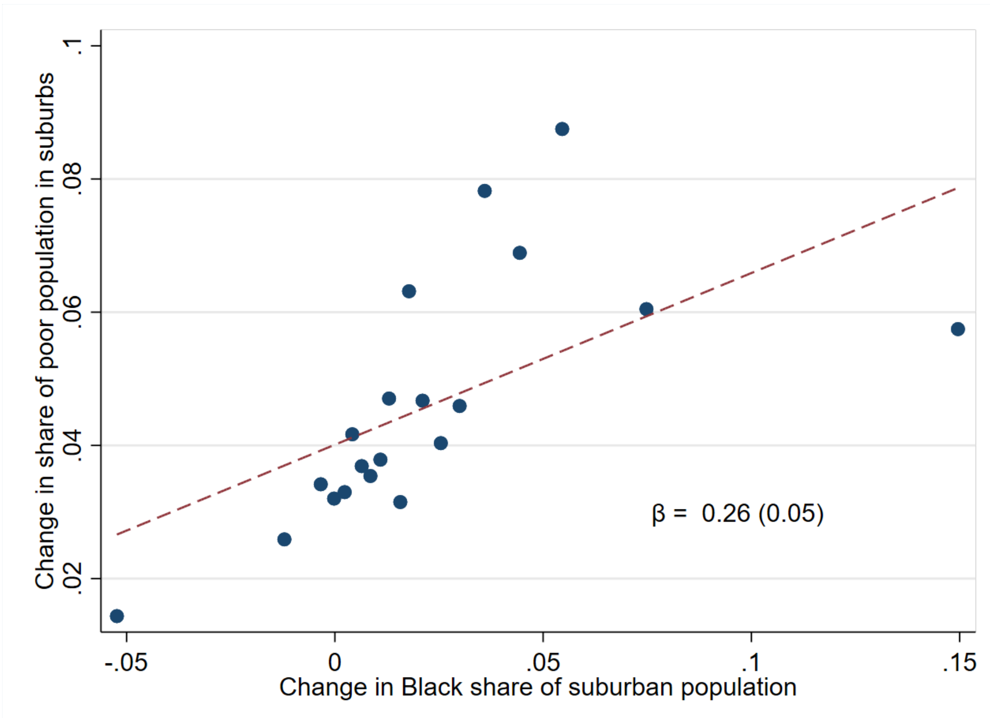
To analyze these variables at the MSA level, we calculate changes between the 1990 decennial census and the 2015–2019 five-year ACS. Our measure of the change in suburban poverty is the percentage-point change in the share of an MSA's poor population that lives in the suburbs. We measure the change in the presence of rich and college-educated residents in the suburbs in the same way. Since the suburban population increased during this time period, our regressions control for the change in the share of the MSA's total population that lives in the suburbs. Our results then capture an increase in the poor (or rich, or college-educated) 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 Black suburbanization and suburban poverty in our full sample of MSAs in Appendix Table A.2 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.

[9] 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).

To determine the relationship between these variables at the MSA level, we first 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 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.

Although the vast majority of Black suburban residents are not poor,[10] 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.3. 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

[10] See Appendix Table A.3. We calculate 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

and is not simply due to a mechanical effect of poorer Black residents moving to the suburbs.

A different pattern prevails for the relationship between Black suburbanization and the rich suburban population. We regress the change in the share of rich non-Black households that live in the suburbs on the change in the suburban Black share, controlling for the change in the suburban share of the MSA's non-Black population. Our results, summarized in Appendix Figure A.4, demonstrate that Black suburbanization has a statistically significant negative correlation with changes in the share of rich non-Black households that live in the suburbs (t=-2.8). Suburban areas with larger increases in their Black population had relative declines in their rich non-Black population.

It is possible that factors that we do not include in our regressions drive the relationship between Black suburbanization and changes in the suburban income distribution. For example, this relationship could exist even if changes in the income distribution and growth in the Black suburban population were not directly related if Black families chose to move into suburban areas that were already becoming poorer or to avoid suburban areas that were already becoming richer. We use an instrumental variables strategy, discussed in greater detail in Section 4, to address these concerns.

Finally, one may wonder why we have found evidence that changes in the suburban income distribution, especially among non-Black residents, is related to Black suburbanization. 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 change the distribution of income among suburban residents. Our model demonstrates that an increase in the number of Black suburban residents can lead poorer non-Black residents to move to the 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. Relative to their model, 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 more accurately predict suburban residential patterns.

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: $Y_w \sim \text{Uniform}(0, \gamma)$ and $Y_b \sim \text{Uniform}(0, 1)$, where we set $\gamma = 1.1$. We add a property tax at rate $t = 0.01$, and tp^j captures the quality of the public good in jurisdiction j.

Our functional form for D_r^j is very similar to that in Banzhaf and Walsh (2013), but revised to ensure a nonnegative value. This functional form is based on a "bliss point" for demographic composition, with parameters $\phi_w = 0.9$ and $\phi_b = 0.5$ 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, and s_b^j the share of residents of jurisdiction j that belong to group b, we set

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

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. Their findings illustrate the tradeoff 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.[11]

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 also home to wealthier residents (especially from group b, all of whom live in the city). In this equilibrium, average income is higher in the suburbs than in the city, 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, although 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. Although 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[12] from the 1990 decennial census. The data for this exercise are discussed in greater detail in Section 2. The empirical income distribution indicates 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 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.

[11] 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 describe in Appendix A.3.1 why richer Black and poorer White residents live in the same jurisdiction in racially integrated equilibria.

[12] 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 data from 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 based on 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 offered by the city. While suburban residents were indifferent between the two equally-priced suburban jurisdictions in the first equilibrium, in this equilibrium one suburb is now much richer and more expensive than the other.

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 models' prediction of a racially-divided distribution of income in suburb one and the more uniform (albeit 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 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, however, there are wealthier individuals who live in the city and some wealthy White individuals and poorer Black individuals who live in the poorer suburb. As in the model, there are some impoverished individuals who live in the richer suburb, which primarily consists of wealthy White residents.

Figure 5: Income distribution in the second equilibrium

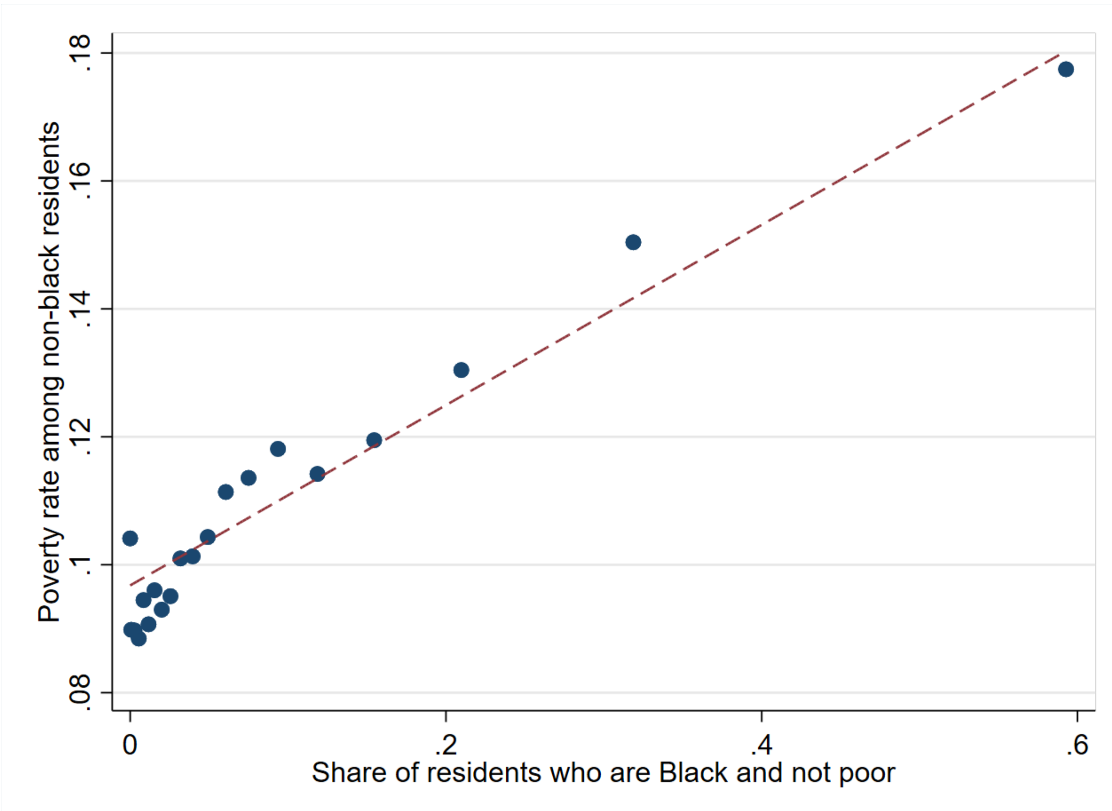
Note: An equilibrium from our modeling exercise is presented on the left. On the right, we use household income data from the 2015–2019 five-year ACS for all urban and suburban census tracts in the Chicago metropolitan area. Frequencies for the Black population in the Chicago area use the scale on the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

3.3 Implications

The results of this simple model demonstrate how the suburbanization of one group can lead to changes in the suburban income distribution, as the movement 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 the same suburban area. Since members of group w do not prefer this demographic composition, housing prices are low in this suburb in this equilibrium. This affordability leads some of poorer members of group w to choose to live there. These theoretical results indicate that changes in housing prices and demographically-influenced movement of the White suburban population between jurisdictions may be important mechanisms by which Black suburbanization leads to changes in the suburban income distribution.

One prediction of this model, as mentioned above, is that wealthier Black residents may live in the same suburban areas as poorer non-Black residents. This prediction is borne out in American suburbs in the 2015–2019 ACS. As shown in Figure 6, our census-tract data show that the poverty rate among non-Black suburban residents increases with the share of the tract population that is Black and not poor. In the suburbs, richer Black residents are exposed to non-Black poverty.

Figure 6: Poor non-Black residents live with nonpoor 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 live in these suburbs. These predictions are borne out in the wealthier suburbs of the Chicago area, as evidenced by the distribution of race and income in “Suburb 2” in Figure 5.

Although we now know the theoretical rationale for how suburbanization of middle-income Blacks residents may change the geographic distribution of income, 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 by another group. Knowing the size of this relationship empirically will illuminate how much we expect the income distribution to change, and suburban Black residents’ exposure to poverty to increase, as the suburban Black population grows. 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 now want to determine the extent to which the socioeconomic makeup of the suburbs changes in response to Black suburbanization. That is, we want to estimate β in the causal model given by Equation 2, where y_i is one of our measures of the socioeconomic composition of the suburbs. Specifically, we examine the share of the non-Black rich, college-educated, or poor population of MSA i that lives in the suburbs. In the following sections we will examine additional outcomes, which we denote $\tilde{y}_i$, including changes in home prices. We are interested in how these outcomes change in response to changes in x_i, the Black share of the suburban population of MSA i.

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

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 to suburbanize based on their predictions about the evolution of y_i. 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 new shift-share instrument for the change in the Black share of the suburban population between 1990 and 2015–2019. We do so by incorporating the distance between the suburbs and the primary urban Black neighborhood into existing empirical strategies. Specifically, we interact the distance from the primary urban Black neighborhood to the nearest suburb with the instrument for Black population growth in Northern cities as used in Boustan (2010), Derenoncourt (2022), and Cui (2024). As in these papers, we make use of variation in the growth of the Black population between Northern cities induced by the Great Migration of four million Black individuals from the South between 1940 and 1970. Validity of our 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. In decomposing $\varepsilon_i = \gamma\mathbf{c_i} + \epsilon_i$, we control for MSA population in 1990 and census region fixed effects, following Boustan (2010). Controlling for population and census region allows us to analyze changes in the suburban income distribution 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 augment the standard instrument for growth in the Black population in Northern cities by incorporating the distance between the largest urban Black neighborhood and the nearest suburb. The standard shift-share instrument for changes in the Black population of Northern cities uses variation in the strength of migrant networks between Northern cities and Southern counties in 1940 along with variation in the amount of Black out-migration across Southern counties between 1940 and 1970. Incorporating our city-to-suburb distance term into this instrument, we can 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 suburban-distance 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,

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

We use Boston and Cleveland to provide a simplified example of how we combine the shifts and shocks to construct z_i. In Appendix Table A.4, 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. By computing the instrument z_i for each city as the weighted average of growth in migration $\sum_k s_{ik} g_k$, we predict that 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 later show in our analysis of the first stage of the instrument.

To strengthen our instrument, we use the regression weight e_i that measures the inverse of the distance to the suburbs. All else equal, we expect MSAs in which the suburbs are closer to the largest urban Black neighborhood to feature a larger increase in the Black suburban population. This happens because Black suburbanization often began in suburbs close to the 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 greater detail in Appendix A.3.3. 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 the income distribution 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[13]. 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.

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

Although we cannot explicitly test the exclusion restriction, we conduct pretrend tests, as recommended by Borusyak et al. (2022), in which we replace our main outcome variables with the outcome for the period prior to our analysis. We estimate Equation 10, instrumenting for x_i with z_i[14]. A statistically significant coefficient δ would indicate that our instrument is correlated with an unobserved confounding variable, violating the exclusion restriction.

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

The results of the pretrend test for suburban poverty supports 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,

[13] 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).

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

the estimates of δ in Table 1 are not significant. In addition to lacking statistical significance, these coefficients are also approximately one order of magnitude smaller than in our main results.[15] Pretrend tests for non-Black suburban and college-educated share show similar results, as displayed in Appendix Tables A.5 and A.6 respectively.

Table 1: Pretrend 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 2015–2019. Control variables at the MSA level are total population in 1990 and census region fixed effects. Regression weights in column three are based on MSA population in 1990. All columns in 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 shock level to obtain correct standard errors.[16] We follow their suggestion with our sample of 1,174 Southern counties[17], as described below. Therefore, the units of observation in our regressions are Southern counties that sent Black migrants to Northern MSAs. There are 97 Northern MSAs represented in this sample.

[15] Borusyak et al. (2022) also suggest testing the control variables for balance by using them as the dependent variables in Equation 10. In 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.

[16] 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.

[17] 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. Although our sample includes 1,174 counties, our effective sample size using county-level shocks is 142.

To estimate the shock-level regression, we convert our MSA-level measures of changes in suburban outcomes and Black suburbanization from Equation 3 to the level of the shocks.[18] 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:

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

While we obtain our results from estimating the shock-level Equation 11, the point estimate of β is equivalent to that from 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 change in suburban wealth, poverty, or education levels resulting from a one-percentage-point increase in the Black share of the suburban population.

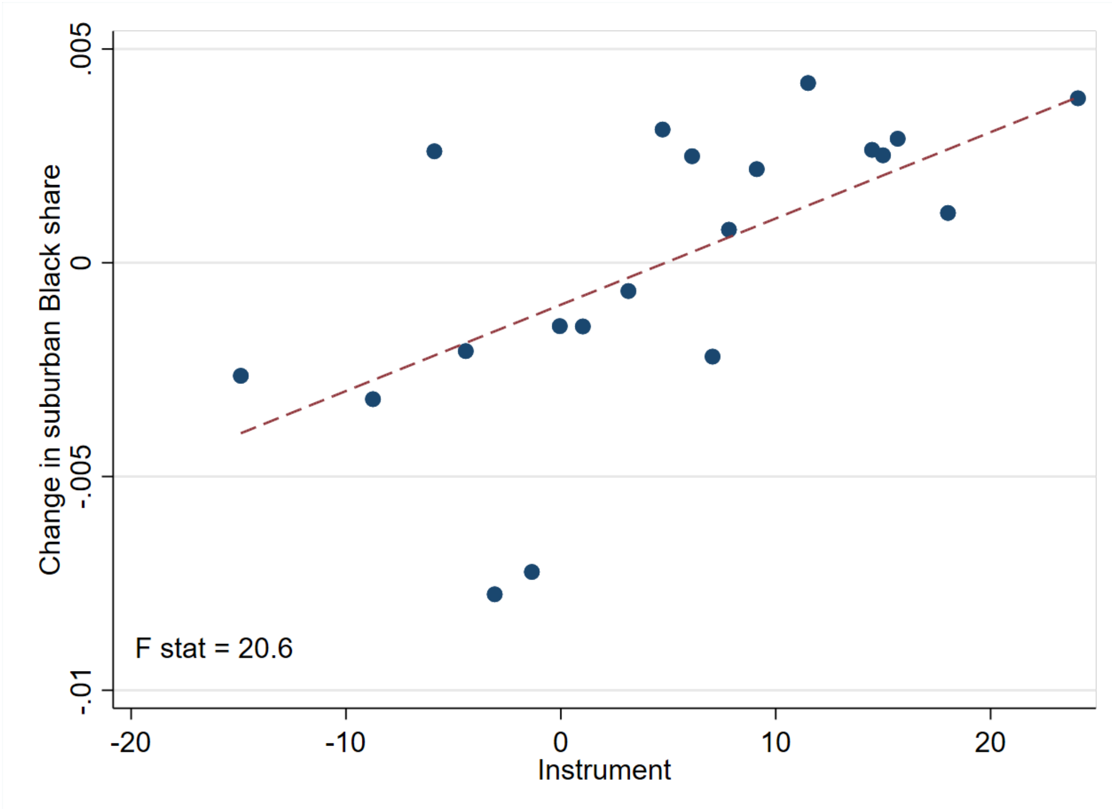
Finally, Borusyak et al. (2022) note that if the sum of weighted exposure shares $\sum_k e_i s_{ik}$ is not constant across locations i, one must control for the sum of these shares in the regression. Therefore, we control for the sum of exposure shares, $\sum_k e_i s_{ik} = \sum_k s_{ik}/d_i$, in our 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 significant relationship with Black suburbanization. F-statistics for each specification are included in our tables of results.

[18] 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 rich and college-educated non-Black residents become less likely to live in the suburbs, while impoverished non-Black residents become more likely to live in the suburbs, in response to Black suburbanization.

We provide causal estimates of the change in the share of the rich[19] non-Black metropolitan-area population that lives in the suburbs in response to Black suburbanization. In Table 2, we display our results from estimating Equation 11 as a shock-level IV regression of the change in the share of rich non-Black residents living in the suburbs on the change in the Black share of the suburban population. We control for the sum of exposure shares in each specification. Although 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 negative and significant throughout.

[19]These results are robust to a variety of definitions of "rich".

Our results in Table 2 indicate that Black suburbanization causes the proportion of the rich non-Black population that lives in the suburbs to decline. The independent and dependent variables in this regression are both changes in shares, so the magnitude of the coefficient in column two implies that a one-percentage-point increase in the Black share of the suburbs causes the share of the rich non-Black population that lives in the suburbs to decrease by approximately one percentage point. These results suggest that wealthier non-Black suburban residents left the suburbs as Black residents moved in. These coefficients are larger than for a similar regression estimated on the nonpoor population (i.e., on all individuals with incomes above the poverty line) in Appendix Table A.8, which supports the descriptive findings of Kye (2018) and Parisi et al. (2019) that the "flight" response to Black suburbanization increases with income.

Table 2: Black suburbanization and rich suburbanites

	Non-Black suburban rich		
	(1)	(2)	(3)
Change in suburban Black share	-0.666***	-1.041***	-1.826***
	(0.199)	(0.331)	(0.704)
Observations	1174	1174	1174
Control Variables	No	Yes	Yes
Suburban Distance Weighting	No	No	No
Population Weighting	No	No	Yes
Effective F-statistic for IV	11.6	14.6	5.5

Note: Exposure-robust standard errors are clustered at the shock (Southern county) level. The dependent variable is the change in the share of non-Black metropolitan-area households with household income above $25,000 in constant 1980 dollars that lives in the suburbs between 1990 and 2015–2019. 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. Regression weights in column three are based on MSA population in 1990. *** indicates significance at the 1% level.

We next show that educational attainment of the non-Black population decreases as a result of Black suburbanization as well. This decline in the fraction of non-Black college-educated individuals who live in the suburbs suggests that the college-educated population moved away from the suburbs in response to Black suburbanization. The magnitude of the coefficient in column two of Table 3 implies that a one-percentage-point increase in the Black share of the suburbs causes the share of the non-Black college-educated suburban population to decrease by 1.1 percentage points.

Table 3: Black suburbanization and suburban education

	Non-Black suburban education		
	(1)	(2)	(3)
Change in suburban Black share	-0.754**	-1.098**	-2.378***
	(0.318)	(0.535)	(0.811)
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 MSA's non-Black population with a college degree or higher that lives in the suburbs between 1990 and 2015–2019. The independent variable is the change in the suburban Black share between 1990 and 2015–2019. Control variables at the MSA level are total population in 1990 and census region fixed effects. Regression weights in column three are based on MSA population in 1990. *** indicates significance at the 1% level.

Turning to the other end of the income distribution, we demonstrate that suburban poverty increases as a result of Black suburbanization. The interpretation of the coefficients in Table 4 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 when clustering the exposure-robust standard errors at the state, instead of county, level (Appendix Table A.9), and if the instrument does not account for the distance to the suburbs (Appendix Table A.10). The instrument is stronger when we include the suburban-distance regression weighting $e_i = d_i^{-1}$.

Our estimates in Table 4 allow us to determine how much suburban poverty increased due to Black suburbanization. The coefficient in our preferred specification (column two) implies that the mean increase in the Black share of the suburban population across MSAs in our analysis sample (2.1 percentage points, in Appendix Table A.2) caused an increase in the share of the metropolitan-area poor population that lives in the suburbs of $2.1 * 2.345 = 4.9$ percentage points, which is approximately $\frac{4}{5}$ of the mean increase in the share of poor residents living in the suburbs across MSAs in our analysis sample of 6.1 percentage points.

Table 4: Black suburbanization and suburban poverty

	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 between 1990 and 2015–2019. The independent variable is the change in the suburban Black share between 1990 and 2015–2019. Control variables at the MSA level are total population in 1990 and census region fixed effects. Regression weights in column three are based on MSA population in 1990. In Appendix Table A.10, 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.

To remove any mechanical effects by which Black suburban residents increased suburban poverty, we next measure suburban poverty among only the non-Black suburban population. The effects of Black suburbanization on non-Black suburban poverty are positive and statistically significant. Our results in Table 5 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 remain significant when clustering the exposure-robust standard errors at the state, instead of county, level, although the coefficient in column three loses significance (Appendix Table A.11).

Table 5: Black suburbanization and non-Black suburban poverty

	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 between 1990 and 2015–2019. The independent variable is the change in the suburban Black share between 1990 and 2015–2019. Control variables at the MSA level are total population in 1990 and census region fixed effects. Regression weights in column three are based on MSA population in 1990. In Appendix Table A.10, we 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 MSAs in which more Black residents moved to the suburbs. Furthermore, these results quantify the undue exposure to suburban poverty that Black suburban residents face. The coefficient in our preferred specification (column two) indicates that, in an MSA in our analysis sample with the average increase in the Black share of the suburban population (2.1 percentage points), Black families moved into suburban areas where the share of the non-Black poor population that lived there was $2.1 * 1.285 = 2.7$ percentage points higher than it would have been were there no relationship between Black suburbanization and non-Black suburban poverty.

Finally, we note that our estimated IV coefficients are consistently larger than the OLS coefficients. The relevant coefficients using OLS are 1.21 for column two of Table 4 and 0.60 for column two of Table 5. These OLS coefficients are approximately half of the size of the corresponding IV coefficients, indicating that omitted variable bias attenuated the OLS coefficients. One explanation for this downward bias is that Black suburbanites endogenously chose suburbs that subsequently experienced relatively smaller increases in poverty.

6 Mechanisms: Neighborhood Change

We now investigate the mechanisms by which Black suburbanization changed the spatial distribution of income. A decrease in the rich, college-educated suburban population does not necessitate an increase in the impoverished population. However, our theoretical model demonstrates how demographic tastes, changes in home prices, and the relocation of richer and poorer individuals between the city and suburbs can increase poverty in the suburban areas into which Black residents move. In this section, we empirically examine changes in home prices and the resulting change in suburban demographics.

6.1 Affordable Homes Decrease in Price

We use our instrument to investigate the effect of Black movement to the suburbs on suburban home prices, as research about historic episodes of Black migration has demonstrated that home prices tend to decrease with Black in-migration (Daepp, Hsu, et al. 2023). Since we documented that the share of the rich and college-educated non-Black population that lives in the suburbs declines with Black suburbanization, we may also expect demand for suburban housing and home prices to decline. To understand the relevant segment of the housing market for lower-income individuals, 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 come 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 for MSA i. Similarly to the previous section, we display our results from estimating Equation 11 as a shock-level IV regression of the change in $\tilde{y}$ on the change in the Black share of the suburban population.

Table 6: Black suburbanization and suburban home prices (25th percentile)

	Bottom quartile 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 between 1990 and 2015–2019. The independent variable is the change in the suburban Black share between 1990 and 2015–2019. Regression weights in column three are based on MSA population in 1990. 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 the 25^{th} percentile of suburban home prices to grow less quickly. Given the units, the coefficient in column two 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. This coefficient implies that a 2.1-percentage-point increase in the Black share of the suburban population (the mean increase across MSAs in our analysis sample) caused bottom-quartile suburban home prices to grow by 28.9% 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 there.

6.2 Entry of Lower-Income Residents

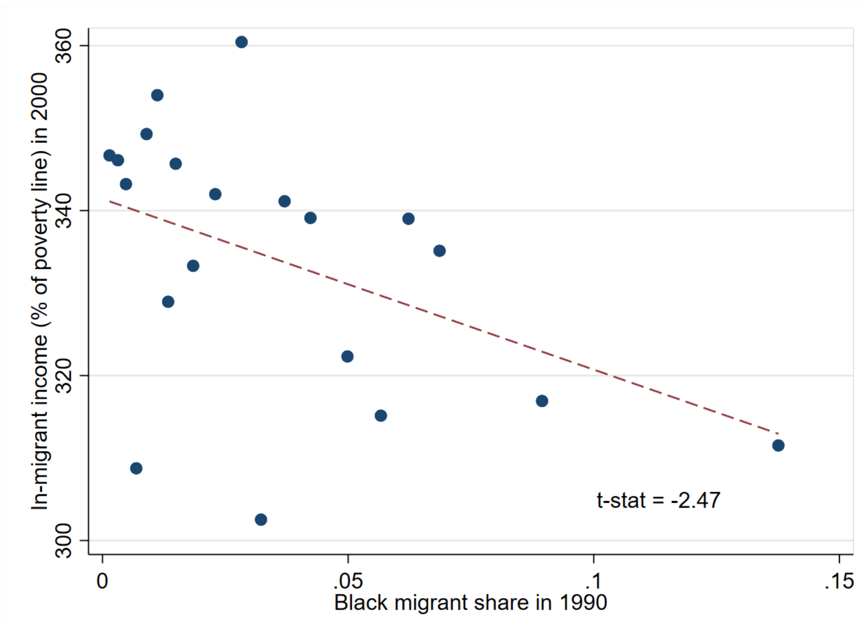
Given the depressed growth in suburban home prices documented above, suburban areas with more Black in-migrants became relatively more affordable. We now provide suggestive evidence that lower-income individuals moved into these suburbs with new Black residents.

Unlike in the previous subsection, here we need to separate incumbent suburban residents from individuals who moved into the suburbs. Publicly available census microdata can distinguish movers from incumbent residents, but its finest level of geography is the Public

Use Microdata Area (PUMA).[20] 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 rather than a causal analysis.

We find a negative correlation between Black in-migration and subsequent in-migration of lower-income individuals when analyzing suburban CONSPUMAs.[21] We use Census and ACS microdata to create our dependent variable, which is the average income of individuals who moved into suburban CONSPUMAs between 1995 and 2000, expressed relative to the poverty line. Our independent variable is the share of residents of each suburban CONSPUMA who were Black in-migrants in 1990. The binscatter in Figure 8 indicates that the average income of individuals who moved into suburban CONSPUMAs decreased as the Black migrant share of the CONSPUMA increased. Although this relationship may not be causal, it suggests that poorer individuals followed Black residents into the suburbs.

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 residents of suburban CONSPUMAs in 2000 declines as the share of CONSPUMA residents in 1990 who are new Black residents increases.

[20]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.

[21]A CONSPUMA is a PUMA with constant boundaries over time. Using CONSPUMAs allows us to analyze changes in the population characteristics of a given area over time.

Taken together, the evidence we have presented demonstrates that the suburban income distribution transformed due to a process of neighborhood change: Black suburbanization leads wealthier and better-educated incumbent residents 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 report that our main results and mechanisms by which we find that Black suburbanization changes the spatial distribution of income are broadly robust to changing the spatial scale or timing of our analysis. We construct a new instrument based on spatial patterns of Black suburbanization and demonstrate that growth in the Black population of specific suburbs shifts the income distribution of non-Black residents living there.

7.1 Robustness to Spatial Scale: Within-MSA Analysis

With the exception of the Section 6.2, our analysis thus far has focused on changes that occur between MSAs. However, Lichter et al. (2023) suggests that some incumbent suburban residents respond to Black suburbanization by moving to different suburbs within the same MSA. In this section we construct a new instrument to focus on how home prices and poverty change 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.

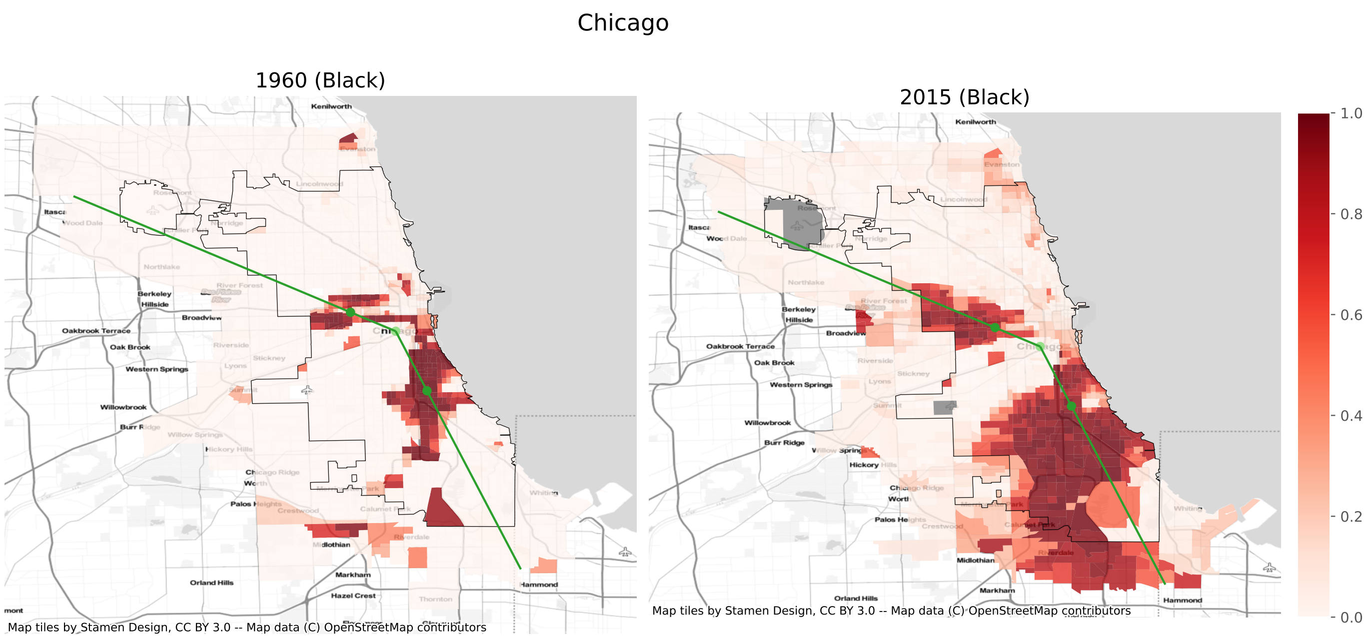
To construct our instrument, we build on a nascent literature in urban economics, exemplified by Davis et al. (2024) and Sood and Almagro (2024), that exploits the interplay between the geographic and demographic structure of cities. Our instrument is built on our empirical observation that Black residents 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.[22]

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

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)[23] and extend this ray out towards the suburbs. This ray represents the direction in which we predict that 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, then extend it outwards. When we examine 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.

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.

[23] 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.

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 ray and the center of the tract. We then aggregate the tracts into groups due to the high degree of racial segregation at the tract level. 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 we then use these groups of tracts[24] as our unit of analysis. Our instruments are then the average distance along the ray and the average distance to the ray among tracts within a tract-group.

We want to analyze how changes in non-Black poverty and home prices between suburban areas within MSA i respond to growth of the Black population using the causal model of Equation 12. For a given outcome y_j, we estimate β using IV regression with instrument z_j:

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

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

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

Our exclusion restriction requires that, within an MSA, the average distance for a tract–group along the ray from the center of the urban Black neighborhood to the closest point on 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 a ray constructed based on the location of the urban Black neighborhood and CBD, lends credibility to this assumption. We further assess this assumption with pretrend tests that are reported in our tables of results.

7.1.2 Within-MSA changes in home prices

Though our between-MSA analysis from Section 6.1 found that the bottom quartile of suburban home prices declined in MSAs with more Black suburbanization, we want to further examine local changes in home prices 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 use our instrument z_j to estimate Equation 12 and quantify the relationship between Black in-migration and suburban home prices. Here, y_j is the change between 1990 and

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

2015–2019 in the median home price[25] 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 come from the 1990 decennial census and 2015–2019 ACS.

We conduct a pretrend test on our instrument in columns one and two of Table 7 to determine whether home prices were on different trends in tract–groups with higher versus lower values of the instrument prior to our 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, diminishing the validity of this empirical approach. Fortunately, our estimated coefficients in the pretrend test in Appendix Table A.14 are statistically insignificant.

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 Table 7 are negative and significant. The magnitude of these coefficients indicates that an additional percentage-point increase in the Black share of the population of the tract–group between 1990 and 2015–2019 decreased growth in median home prices by approximately 2% relative to other suburban tract–groups within the same MSA. These results support our findings that home prices decline due to Black suburbanization, which we now show holds even between suburban areas in the same MSA.

Table 7: Within-MSA home price changes

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

Note: Observations at the suburban tract-group level. Regressions exclude suburban tracts 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 is reported in percentage points. Conley standard errors are used in all columns. *** indicates significance at the 1% level.

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

7.1.3 Within-MSA changes in non-Black poverty

We next investigate whether our MSA-level result that non-Black suburban poverty increases as Black residents move to the suburbs also holds between suburban neighborhoods within an MSA. Here, we use z_j to 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 is the change between 1990 and 2015–2019 in the share of residents of tract group j who are Black. Data for these variables come from the 1990 decennial census and 2015–2019 ACS.

Our regression results indicate that, even within an MSA, non-Black poverty increases in the same suburban neighborhoods that Black residents moved into. The coefficients in Table 8 are positive and significant. The magnitude of these coefficients indicates that the non-Black poverty rate increased by approximately 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 8: Within-MSA changes in non-Black poverty

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

Note: Observations at the suburban tract-group level. Regressions exclude suburban tracts far from the closest urban Black neighborhood and those in the opposite direction from the center city. The dependent variable is the change in 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.

Appendix Table A.15 displays the results of our the pretrend test. In the pretrend test, y_j measures changes in the non-Black poverty rate between 1980 and 1990. While the coefficient in column one is significant, it is less than half the magnitude of its contemporaneous counterpart in Table 8 and presents lower levels of significance. Though this pretrend diminishes the exogeneity of this instrument, our results indicate that non-Black poverty still increased as Black families entered 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 analyze how outcomes change between 2000 and 2015–2019 in response to growth in the suburban Black population between 1990 and 2000. Analyzing these subsequent changes in our outcomes removes any mechanical effect that the Black in-migrants themselves had on outcomes during the initial period. That is, this analysis focuses on changes in neighborhoods that are induced by, but not directly or mechanically affected by, the initial Black movement to the suburbs. Results from this analysis show that rich and college-educated non-Black residents became less likely to live in the suburbs, while poor non-Black residents became more likely to live in the suburbs, after the Black share of the suburban population increased.

Our results indicate that wealthier and better-educated non-Black residents became less likely to live in the suburbs following increases in the Black suburban population. The coefficients in Appendix Table A.12 indicate that between 2000 and 2015–2019 the share of rich non-Black residents living in the suburbs decreased by approximately 0.8 percentage points and the share of college-educated non-Black residents living in the suburbs decreased by 1.2 percentage points following a one-percentage-point increase in the Black suburban population between 1990 and 2000. The coefficients in this table are all negative and statistically significant, with the exception of column one, and similar in magnitude to our main results from Tables 2 and 3.

Additionally, our results suggest that poorer residents became more likely to live in the suburbs after the Black suburban population grew. Our results in Appendix Table A.13 indicate that between 2000 and 2015–2019 the share of poor residents living in the suburbs increased by approximately two percentage points and the share of non-Black poor residents living in the suburbs increased by 1.5 percentage points as a result of each percentage-point increase in the Black suburban population between 1990 and 2000. These results are all statistically significant, with the exception of column six, and similar in magnitude to our main results from Tables 4 and 5.

The results of this analysis demonstrate that rich and college-educated non-Black residents avoided suburban areas in which the Black share had risen. On the other hand, suburban poverty increased after the Black share of suburban residents rose, thereby increasing Black suburban residents' exposure to poverty.

8 Consequences of Changes in the Geographic Distribution of Income

While we have already documented that suburban poverty increases Black suburban residents' exposure to poverty, in this section we describe additional consequences of the increase in suburban poverty. We discuss how the suburbs create poverty among incumbent residents and briefly outline potential policy responses.

8.1 The Location of Poverty Matters

We analyze the effects of redistributing impoverished individuals across space while holding overall poverty constant. First, impoverished individuals are harmed when poverty-reduction services are harder to access. Second, total property tax revenues may fall if areas in which poor individuals live are particularly dependent on property tax revenue and experience declines in home prices. Third, declines in local public good quality are especially damaging in areas with higher homeownership rates, such as the suburbs.

8.1.1 Spatial mismatch between poverty and services

Many services designed to help those in poverty are provided at the local level. However, an 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) summarizes research on this spatial mismatch:

"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 antipoverty programs (Allard 2017).

The gap in antipoverty resources between urban and suburban areas is large and growing.

More than two-thirds of all nonprofit human services expenditures occur in urban areas (Allard and Pelletier 2021), and expenditure growth was higher in urban than suburban counties between 2000 and 2017, even as suburban poverty expanded. The gap in resources produces 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." Although this mismatch between service need and provision is detrimental, we are unaware of evidence demonstrating a link between suburban residence and 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 needed and provided, 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.

We find a negative 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[26] 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 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 find a negative, though less significant, relationship with property tax receipts for the MSA as a whole. In this regression, we control for the growth in the MSA's population.[27] We show in Appendix Figure A.6 that an increase in suburban poverty decreases growth in the MSA's total property tax receipts, although this effect is only marginally 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. While 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

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

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

revenue.

8.1.3 Public good quality

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.[28] 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.

To measure school quality, we use data from NCES on the high school completion rate of school districts[29] 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.

We find that there is a statistically significant negative relationship between the change in school quality and the change in suburban poverty rates.[30] Our results at the MSA level are displayed in Appendix Figure A.7. Due to the presence of peer effects in education, a decline in school quality may effect residents throughout the school district. While we do not claim that the relationship between suburban poverty and school quality is causal, a decline in school and amenity quality in suburban areas due to an increase in poverty would decrease overall well-being.

8.2 Poverty Creation

Although our mechanisms analysis indicates that Black suburbanization increases suburban poverty through sorting, we discussed in Section 2.2.3 that the suburbs have both created and attracted poverty since 1990. However, Black suburbanization cannot explain the entire increase in suburban poverty[31] nor the increase in poverty among incumbent suburban residents, which we do not believe is due to sorting. Our estimates from Appendix Table A.1 indicate that incumbent suburban poverty has, on net, increased by almost 1 million people since 1990.

[28] See Appendix A.3.5 for an alternative explanation.

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

[30] 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.

[31] 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.

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 some suburban neighborhoods have decreased. If the average education level of one's 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 increases the income of low-skill workers by 1.9%.

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 $2.8 * 1.9 = 5.3\%$ decrease in income. Assuming that incomes just 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%[32]. Ultimately, 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.

While human capital externalities cannot explain much of the increase in poverty among incumbent suburban residents, a decline in the quality of one's own education or local public goods could affect suburban residents' incomes. We showed in Appendix Figure A.7 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

Although governments may be unable to stop individuals from segregating themselves on the basis of race and income, there are tangible policies that local governments can implement to ameliorate the effects of suburban poverty. Regional governments could start by addressing limited capacity in suburban antipoverty programs, property tax shortfalls, and changing conditions in suburban schools.

While 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 attempt to reduce the impact that poverty has on communities by loosening the connection between local property values and school

[32] $1.056 * (1 - .053) \approx 1$

quality. A system involving more centralized financing of schools and local public goods may lessen the effect that poverty has on the amenities and welfare that suburban residents enjoy.

9 Conclusion

In this paper, we explore whether the growth in the Black, predominantly middle-income, suburban population changes the spatial distribution of income. Our model of residential choice demonstrates how preferences for demographic composition lead to equilibria in which poorer non-Black residents live in the same suburban areas as richer Black residents. Empirical results using our novel shift-share instrument show that the share of rich and college-educated non-Black individuals living in the suburbs decreases and the share of poor individuals living in the suburbs increases as a result of Black suburbanization. We document a process of neighborhood change in suburbs that Black families enter, as we show that wealthier residents sort away from the suburbs, bottom-quartile home prices decline, and lower-income individuals move in. These results and key mechanisms hold across suburban areas within MSAs, between MSAs, and across time periods.

While millions of Black families moved to the suburbs to improve the quality of their neighborhoods, destination responses and an ongoing processes of neighborhood demographic change increase their exposure to poverty. As Derenoncourt (2022) demonstrated 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 nonpoor Black suburban resident than for the average nonpoor White suburban resident. Given that living in a lower-poverty neighborhood provides many benefits to children (Chetty et al. (2016), Chyn and Katz (2021)), the unequal burden of suburban poverty may affect the welfare not only of suburban Black adults but also their children.

Addressing changes to the suburban income distribution will be beneficial not only for the suburban poor but also for their communities. Although it is difficult for policymakers to address sorting and segregation, regional governments can increase revenue sharing to alleviate pressures on tax revenues and public good quality in poorer municipalities. While many suburbs lack effective antipoverty programs (Allard 2017), there are existing poverty-reduction programs that suburbs could implement. However, since most research about these programs has been conducted in urban areas, we do not yet know if these approaches would be effective 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 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

Note: Numbers in millions. Data from Census and ACS microdata. Methodology for calculating these numbers explained in Sections 2.2.3 and A.3.4. 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.2: Demographic changes in the suburbs, 1990 to 2015–2019

	Full sample		Analysis sample	
	Mean	Std. Dev	Mean	Std. Dev
Change in share of impoverished population in suburbs	0.046	0.053	0.061	0.049
Change in share of population in suburbs	0.036	0.044	0.041	0.035
Change in Black share of suburban population	0.022	0.043	0.021	0.020
Observations	383		97	

Note: Observations are at the MSA level. The analysis sample consists of Northern MSAs used to generate our results with the shift-share IV in Sections 5 and 6. Data from the 1990 decennial census and 2015–2019 ACS.

Table A.3: Suburban poor population

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 for suburban census tracts.

Table A.4: 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 for the given MSA between the 1990 decennial census and 2015–2019 ACS.

Table A.5: Pretrend test: Suburban wealth

	Change in suburban non-Black rich		
	(1)	(2)	(3)
Change in suburban Black share	-0.101	0.143	0.484
	(0.215)	(0.344)	(0.520)
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 rich non-Black 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 2015–2019. Control variables at the MSA level are total population in 1990 and census region fixed effects. Regression weights in column three are based on MSA population in 1990. All columns in this table include a regression weighting e_i for inverse distance to the suburbs.

Table A.6: Pretrend test: Suburban education

	Change in non-Black education		
	(1)	(2)	(3)
Change in suburban Black share	0.355*	0.635*	0.526
	(0.186)	(0.380)	(0.589)
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 college-educated non-Black 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 2015–2019. Control variables at the MSA level are total population in 1990 and census region fixed effects. Regression weights in column three are based on MSA population in 1990. All columns in this table include a regression weighting e_i for inverse distance to the suburbs.

Table A.7: Robustness: Pretrend test, excluding suburban-distance weight

	Suburban poverty		
	(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 between 1980 and 1990. The independent variable is the change in the suburban Black share between 1990 and 2015–2019. Control variables at the MSA level are total population in 1990 and census region fixed effects. Regression weights in column three are based on MSA population in 1990. In this table, we set $e_i = 1$, meaning that this instrument does not account for distance to the suburbs. *** indicates significance at the 1% level.

Table A.8: Black suburbanization and nonpoor suburban residents

	Change in suburban nonpoor		
	(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 MSA's population above the poverty line that lives in the suburbs between 1990 and 2015–2019. The independent variable is the change in the suburban Black share between 1990 and 2015–2019. Control variables at the MSA level are total population in 1990 and census region fixed effects. Regression weights in column three are based on MSA population in 1990. *** indicates significance at the 1% level.

Table A.9: Black suburbanization and 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 between 1990 and 2015–2019. The independent variable is the change in the suburban Black share between 1990 and 2015–2019. Control variables at the MSA level are total population in 1990 and census region fixed effects. Regression weights in column three are based on MSA population in 1990. *** indicates significance at the 1% level.

Table A.10: Robustness: Black suburbanization and suburban poverty, excluding suburban-distance weight

	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 2015–2019. Control variables at the MSA level are total population in 1990 and census region fixed effects. Regression weights in columns three and six are based on MSA population in 1990. In this table, we set $e_i = 1$, meaning that this instrument does not account for distance to the suburbs. *** indicates significance at the 1% level.

Table A.11: 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 between 1990 and 2015–2019. The independent variable is the change in the suburban Black share between 1990 and 2015–2019. Control variables at the MSA level are total population in 1990 and census region fixed effects. Regression weights in column three are based on MSA population in 1990. *** indicates significance at the 1% level.

Table A.12: Robustness to timing: Non-Black suburban wealth and education

	Non-Black suburban rich			Non-Black suburban college-educated		
	(1)	(2)	(3)	(4)	(5)	(6)
Change in suburban Black share 1990-2000	-0.319	-0.790*	-1.064**	-1.013**	-1.207*	-2.550***
	(0.338)	(0.406)	(0.458)	(0.509)	(0.721)	(0.918)
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	17.5	16.9	7.3	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 rich or college-educated 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. Regression weights in columns three and six are based on MSA population in 1990. *** indicates significance at the 1% level.

Table A.13: Robustness to timing: Suburban poverty

	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 variable 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. Regression weights in columns three and six are based on MSA population in 1990. *** indicates significance at the 1% level.

Table A.14: Pretrend test: Within-MSA home price changes

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

Note: Observations at the suburban tract-group level. Regressions exclude suburban tracts 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 is reported in percentage points. Conley standard errors are used in all columns. *** indicates significance at the 1% level.

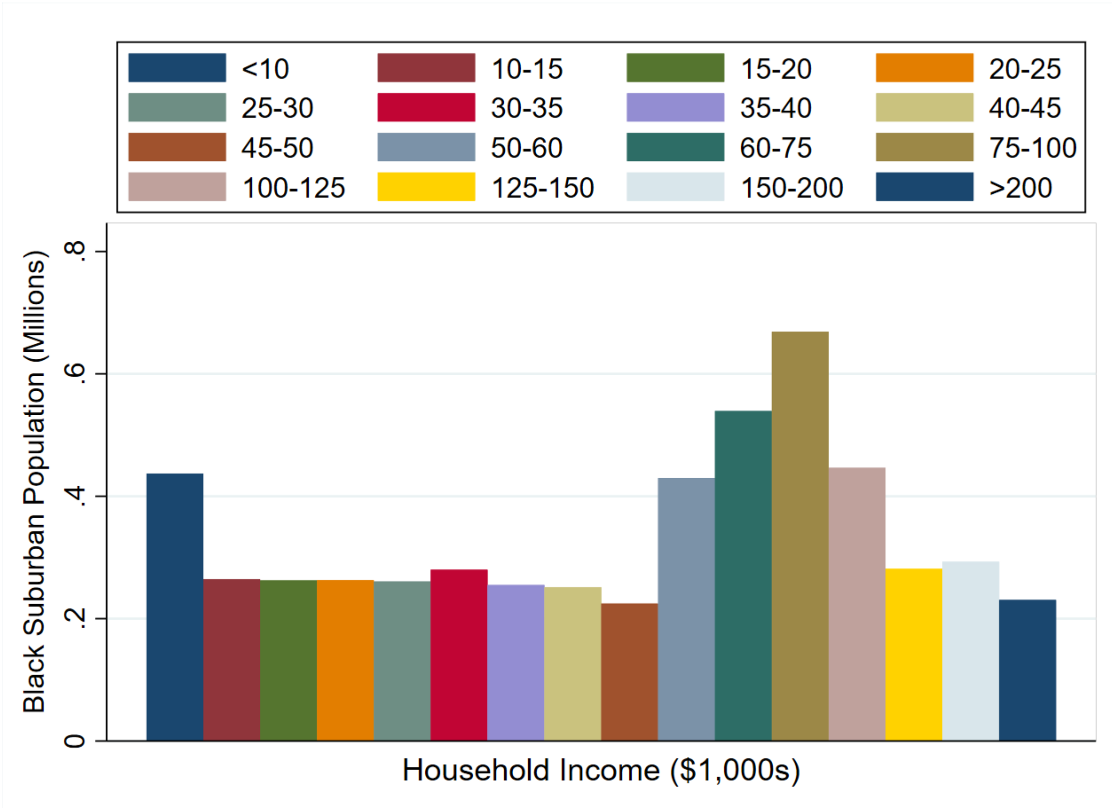
Table A.15: Pretrend test: Within-MSA changes in non-Black poverty

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

Note: Observations at the suburban tract-group level. Regressions exclude suburban tracts far from the closest urban Black neighborhood and those in the opposite direction from the center city. The dependent variable is the change in 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.

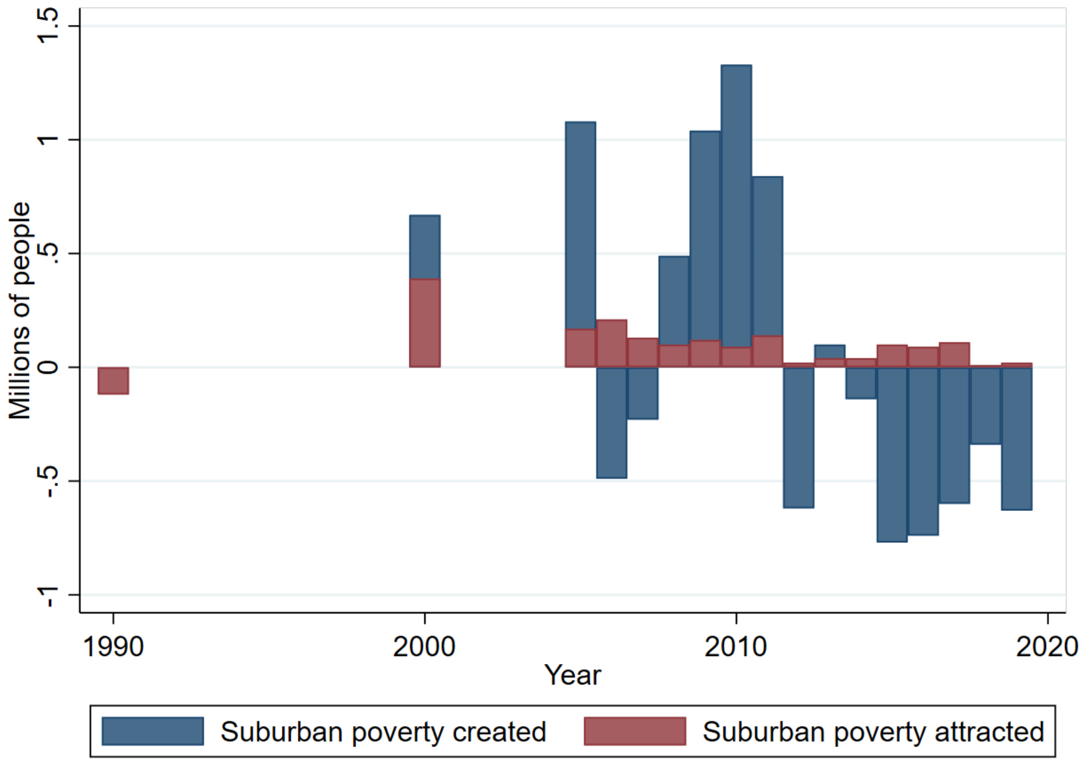
A.2 Appendix Figures

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



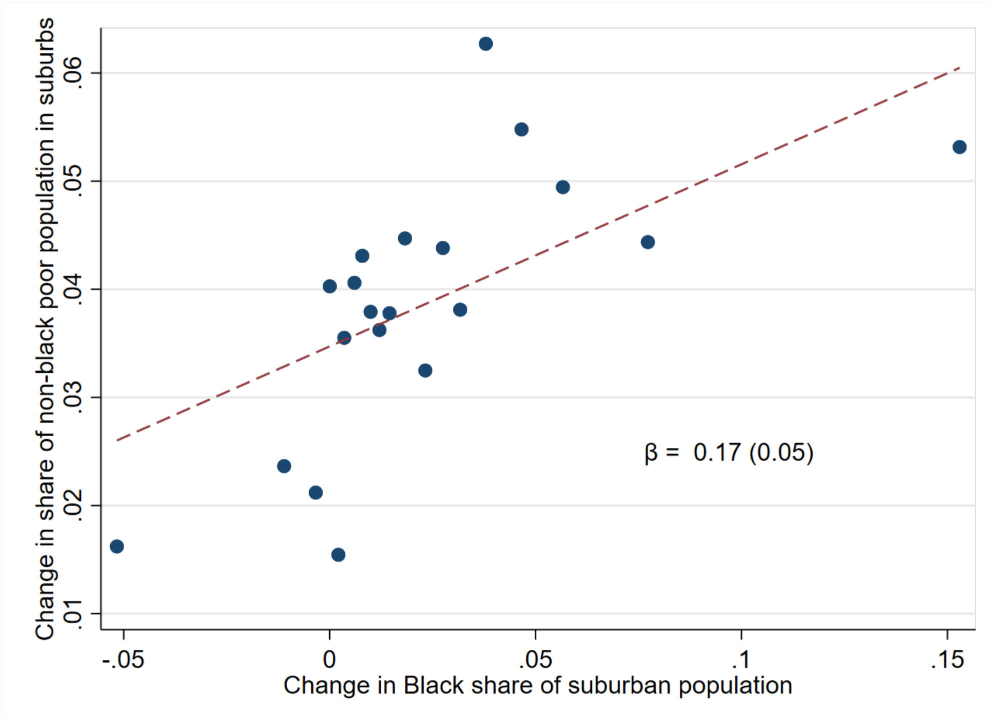
Note: Household income data for Black families for all suburban census tracts in the 2015–2019 five-year ACS.

Figure A.2: Suburban poverty creation and attraction



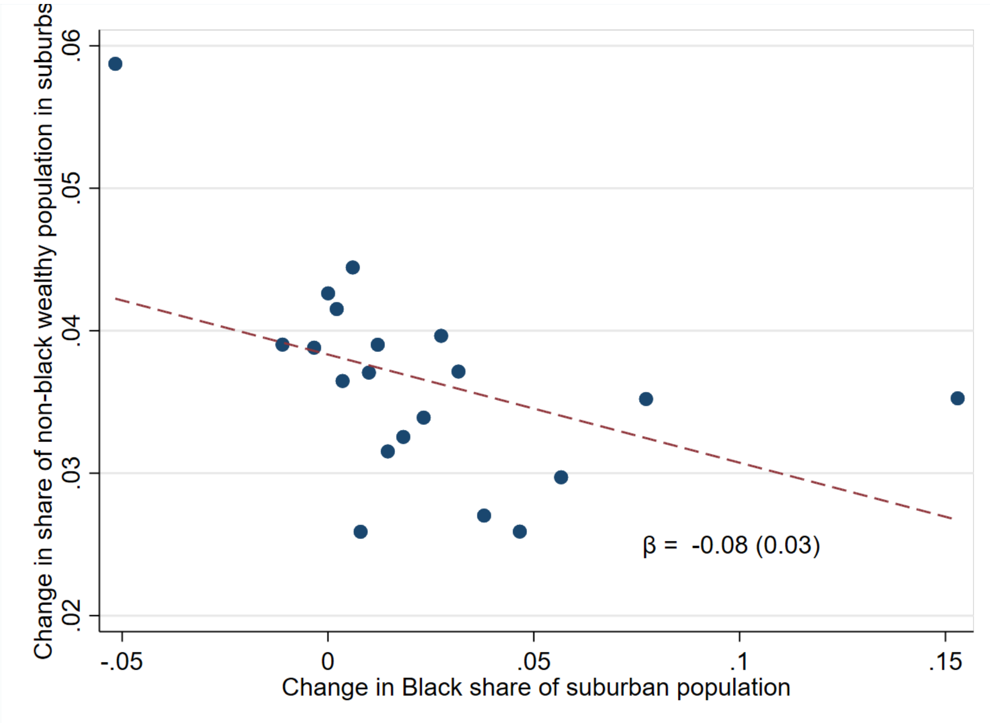
Note: This figure uses microdata from the decennial census (1990 and 2000) and one-year ACS files (2005-2019). We calculate suburban poverty creation as the change in the number of individuals under the poverty line between t and $t-1$ among those who were in the suburbs in year t, and suburban poverty attraction as the net migration into the suburbs of impoverished individuals between periods. These calculations are described in more detail in Sections 2.2.3 and A.3.4.

Figure A.3: Black suburbanization and non-Black suburban poverty



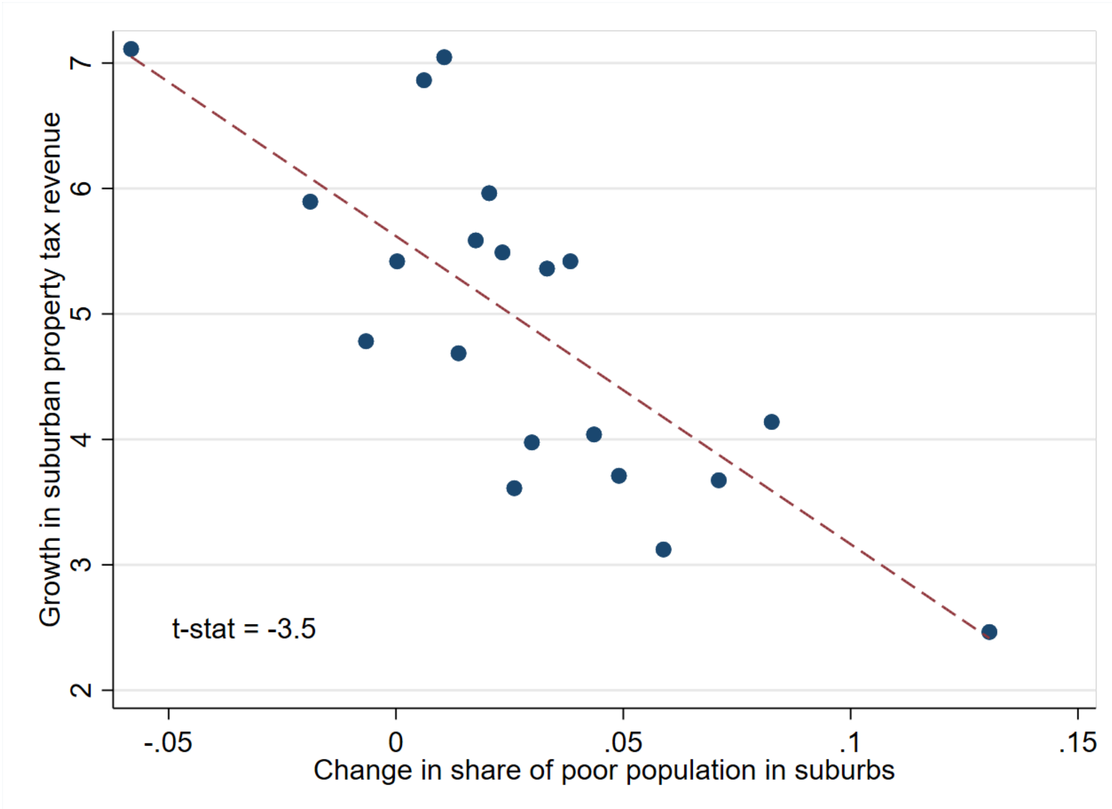
Note: MSA-level binscatter of the change in the share of the non-Black poor population that lives in the suburbs on the change in the share of the suburban population that is Black, controlling for the change in the share of the non-Black MSA population that is suburban. All variables are measured as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

Figure A.4: Black suburbanization and suburban wealth



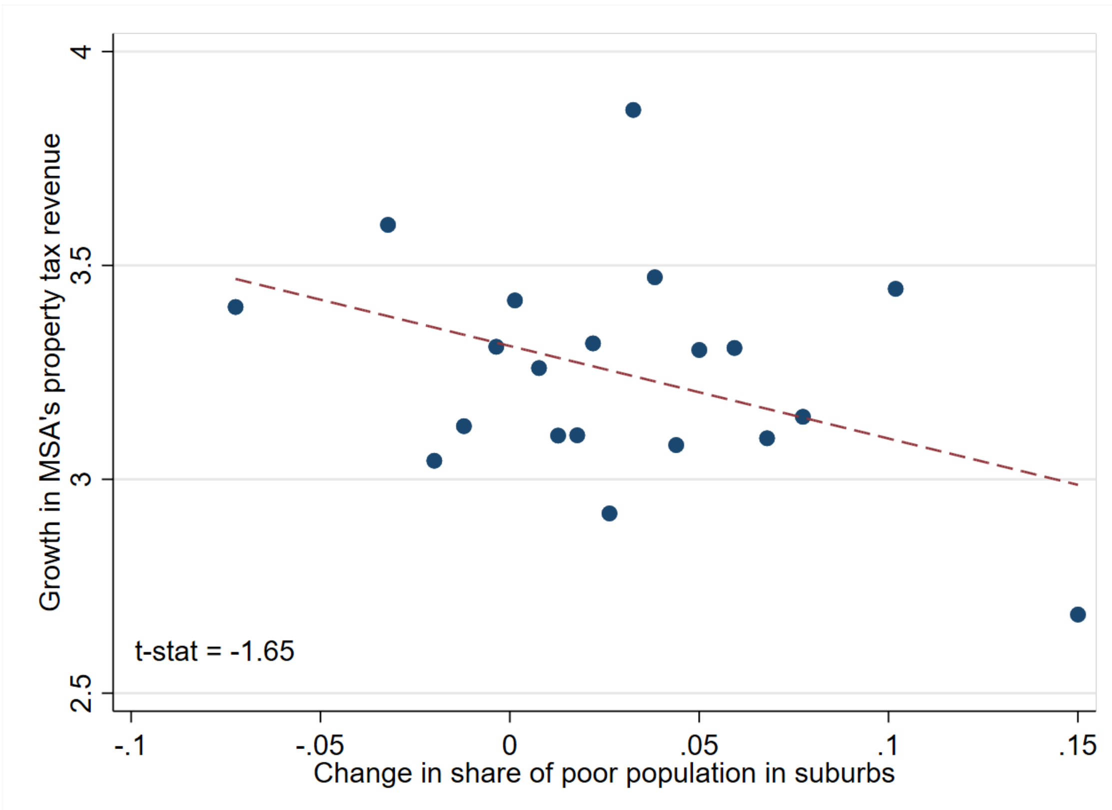
Note: MSA-level binscatter of the change in the share of the rich non-Black population that lives in the suburbs on the change in the share of the suburban population that is Black, controlling for the change in the share of the non-Black MSA population that is suburban. All variables are measured as 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



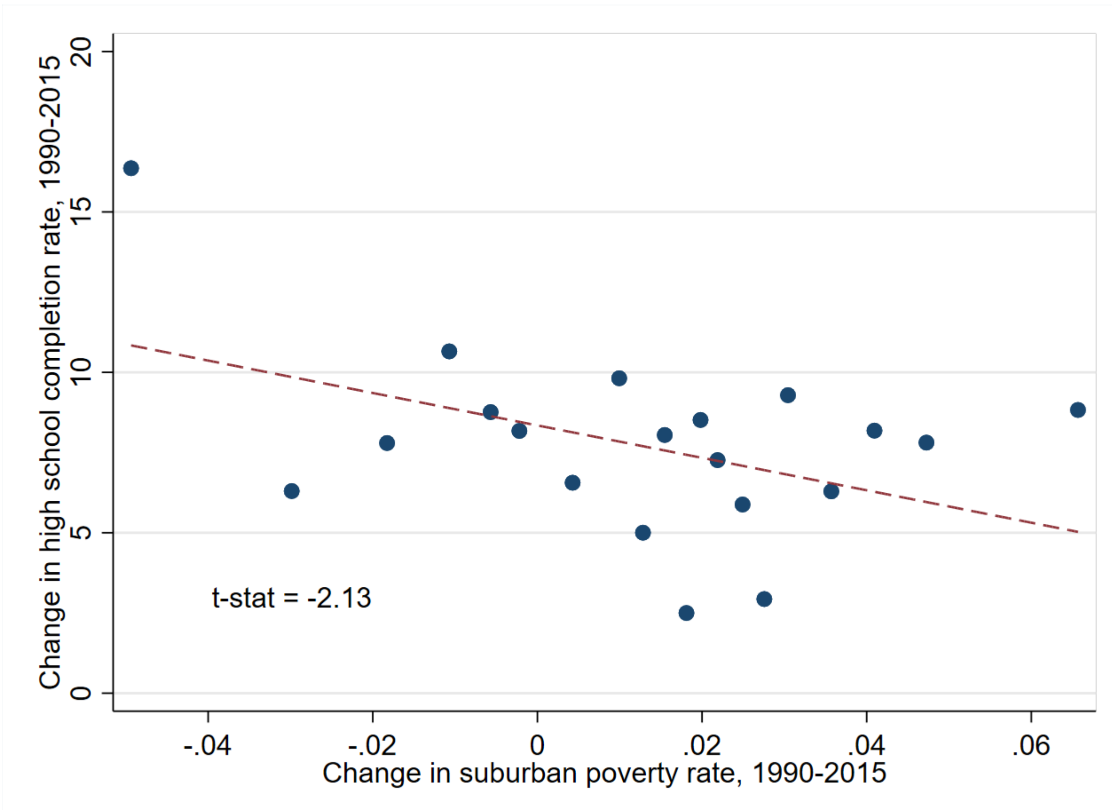
Note: MSA-level binscatter of the relationship between the growth between 1992 and 2017 in the property tax revenue collected in the suburbs of the MSA and the change in the share of the MSA's poor population that lives in the suburbs between 1990 and 2015–2019. Data for the change in suburban poverty 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: Property tax revenue (MSA) and suburban poverty



Note: MSA-level binscatter. Dependent 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 come from the 1990 decennial census and 2015–2019 ACS. Data for municipal property tax revenue are from the Census of Governments, as provided by Willamette University.

Figure A.7: 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 Integrated suburban equilibria

Richer Black residents and poorer White residents live in the same suburban jurisdiction (suburb one) in the second equilibrium in our model simulation. In this section we describe more general conditions under which this equilibrium will occur.
Using the same notation as in Section 3, the difference in utility for a White resident between living in suburban jurisdiction two and suburban jurisdiction one is given by:

$$\begin{aligned} D_w(y) = &\Big(y - (1+t)p^{S2}\Big)^{\alpha}\Big(tp^{S2} + 1 - (s_w^{S2} - \phi_w)^2\Big)^{1-\alpha} \\ &- \Big(y - (1+t)p^{S1}\Big)^{\alpha}\Big(tp^{S1} + 1 - (s_w^{S1} - \phi_w)^2\Big)^{1-\alpha} \end{aligned} \tag{14}$$

For certain values of p^j and s_w^j (for example, when the more expensive jurisdiction has preferable demographic composition), White residents will live in both suburban jurisdictions.[33] In this case, $D(y)$ exhibits a "single-crossing" property: individuals with income y above threshold income $\hat{y}$ choose one suburban jurisdiction, while those with income below $\hat{y}$ choose the other suburban jurisdiction (or the city)[34]. We now show that the richer white residents choose the more expensive suburban jurisdiction in this case. Richer White residents will choose suburb two if $\frac{\partial D_w(y)}{\partial y} > 0$.[35]

$$\frac{\partial D_w(y)}{\partial y} = \alpha\left[\frac{tp^{S2} + 1 - (s_w^{S2} - \phi_w)^2}{y - (1+t)p^{S2}}\right]^{1-\alpha} - \alpha\Big[\frac{tp^{S1} + 1 - (s_w^{S1} - \phi_w)^2}{y - (1+t)p^{S1}}\Big]^{1-\alpha} \tag{15}$$

This derivative is positive if:

$$\Big((1 + tp^{S2}) - (s_w^{S2} - \phi_w)^2\Big)\Big(y - (1+t)p^{S1}\Big) > \Big((1 + tp^{S1}) - (s_w^{S1} - \phi_w)^2\Big)\Big(y - (1+t)p^{S2}\Big) \tag{16}$$

That is, wealthier White residents will choose suburb two if the additional utility derived from its demographic composition outweighs the additional cost. To provide a numeric example, we use the parameter values from our model simulation and second equilibrium from Section 3.2.2, setting $t = 0.01, \phi_w = 0.9, s_w^{S2} = 1$ and $p^{S1} = kp^{S2}$. Simplifying, we have

[33] Formally, this condition is $p^j > p^{j'} > p^{j''}$ and $(s_w^j - \phi_w)^2 < (s_w^{j'} - \phi_w)^2 < (s_w^{j''} - \phi_w)^2$. Otherwise, for example if one jurisdiction is the least expensive and has the most preferred demographic composition, all White residents will live there. Additionally, p^j needs to be low enough that some individuals will choose to live there.

[34] One can obtain the crossing-point $\hat{y}$ by solving $D_w(\hat{y}) = 0$. $D_w(y)$ can have at most one crossing-point value because it is a monotonic function. For certain parameter values, for example if $p^j > p^{j'} > p^{j''}$ and $(s_w^j - \phi_w)^2 > (s_w^{j'} - \phi_w)^2 > (s_w^{j''} - \phi_w)^2$, everyone will want to live in jurisdiction j'' so it will not have any crossing points.

[35] Given $D(\hat{y})_w = 0$, if $\frac{\partial D_w(y)}{\partial y} > 0$, then $D(\dot{y})_w > 0$ for incomes $\dot{y} > \hat{y}$.

$\frac{\partial D_w}{\partial y} > 0$ if:

$$
\begin{aligned}
&p^{S2}\Big(s_w^{S1}(1.818 - 1.01 s_w^{S1}) - 0.9999k + 0.1919\Big) \\
&\quad + y\Big((s_w^{S1}(s_w^{S1} - 1.8) + 0.8\Big) + 0.01 p^{S2} y(1-k) > 0
\end{aligned} \tag{17}
$$

Based on this equation, there are two conditions that need to be satisfied for the wealthier White residents to choose to live in suburban jurisdiction two.
First, we need the price ratio k to be such that $s_w^{S1}(1.818 - 1.01 s_w^{S1}) - 0.9999k + 0.1919 > 0$. In practice, this means that $p^{S1} = kp^{S2}$ needs to be low enough that poorer residents choose to live in suburban jurisdiction one, even though they prefer the demographic composition of suburban jurisdiction two. For $s_w^{S1} = 0.5$, for example, we need $k < \frac{28}{33}$.
Second, we need $s_w^{S1} < 0.8$ in order to satisfy $s_w^{S1}(s_w^{S1} - 1.8) + 0.8 > 0$. This makes intuitive sense, because if $s_w^{S1} > 0.8$, then White residents would prefer the demographic composition of suburban jurisdiction one to that of suburban jurisdiction two (recall $s_w^{S2} = 1$), and the richer residents would the choose to live in suburban jurisdiction one.
Given these two conditions, richer White individuals with $y > \hat{y}$ will choose to live in suburban jurisdiction two, and poorer White residents with $y < \hat{y}$ will live in suburban jurisdiction one (or the city).
The results are similar for Black residents, though none of the Black residents choose suburban jurisdiction two because it is both more expensive and less racially diverse than suburban jurisdiction one. Given the choice between the city and suburb one, though, richer Black residents will choose suburb one under conditions we explore below. Here, let p refer to the cost of living in suburb one and s_b^C be the share of Black residents in the city.

$$
\begin{aligned}
D_b(y) = &\Big(y - (1+t)p\Big)^{\alpha}\Big(tp + 1 - (s_b^{S1} - \phi_b)^2\Big)^{1-\alpha} \\
&- \Big(y - (1+t)p^c\Big)^{\alpha}\Big(tp^c + 1 - (s_b^C - \phi_b)^2\Big)^{1-\alpha}
\end{aligned} \tag{18}
$$

Recalling p^c is normalized to zero, we have:

$$
\frac{\partial D_b}{\partial y} = \alpha\left[\frac{(1 - (s_b^{S1} - \phi_b)^2 + tp}{y - (1+t)p}\right]^{1-\alpha} - \alpha\left[\frac{1 - (s_b^C - \phi_b)^2}{y}\right]^{1-\alpha} \tag{19}
$$

Rearranging terms, this derivative is positive if and only if

$$
y\left[\Big(\phi_b - c\Big)^2 - \Big(\phi_b - s_b^{S1}\Big)^2\right] + p\left[ty + (1+t)\Big(1 - (\phi_b - s_b^C)^2\Big)\right] > 0 \tag{20}
$$

This condition will hold if[36] $(\phi_b - s_b^{S1})^2 < (\phi_b - s_b^C)^2$. That is, given the existence of a crossing point, richer Black residents will live in suburban jurisdiction one when the demographic composition in that jurisdiction is preferable to the demographic composition in the city.

Taken together, then, we have shown general conditions that lead poorer White residents and richer Black residents to live together in suburban jurisdiction one.

A.3.2 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:

$$s_k = \sum_i e_i \, s_{ik}, \; \tilde{\varepsilon}_k = \frac{\sum_i e_i s_{ik} \varepsilon_i}{\sum_i e_i s_{ik}} \tag{21}$$

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:

$$\bar{y}_k^{\perp} = \frac{\sum_i e_i s_{ik} y_i^{\perp}}{\sum_i e_i s_{ik}} \, , \bar{x}_k^{\perp} = \frac{\sum_i e_i s_{ik} x_i^{\perp}}{\sum_i e_i s_{ik}} \tag{22}$$

A.3.3 Ray Construction

The directional ray for each MSA, from the central business district through the primary Black neighborhood(s) and out to the suburbs, is constructed using the first (or second) principal city that has an identifiable place point in 1960[37]. 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.

---

[36] There are other conditions in which this equation will hold, which can be deduced by rearranging Equation 20, but these conditions are less intuitive and not discussed here.

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

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. 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:

$$Centroid_m = \left(\frac{\sum_{t=1}^{T} p_{tm} Lat_{tm}}{\sum_{t=1}^{T} p_{tm}}, \frac{\sum_{t=1}^{T} p_{tm} Long_{tm}}{\sum_{t=1}^{T} p_{tm}} \right) \tag{23}$$

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 23.

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.3.4 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)[38].

To examine transitions into and out of suburban poverty, we group people according to

[38]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.

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

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:

$$\begin{aligned}
&\text{Suburban poverty attraction} + \text{Suburban poverty creation} = \\
&(A + C - G - J) + (B + J - E - F) = \\
&A + B + C - E - F - G = \\
&\text{Change in number of suburban poor}
\end{aligned} \tag{24}$$

We use the microdata described in Section 2.2.3 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.3.5 Effect of home prices on homeowners

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

$$V_{ij} = (Y_i - p_j)B_j\epsilon_{ij} \tag{25}$$

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:

$$V'_{ij} = (Y_i + \kappa p_j)B_j\epsilon_{ij} \tag{26}$$

Note that for someone who owns a home in j, changes in p_j do not affect their payment for housing[39], 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 $\frac{dV'}{\partial p_j} > \frac{dV}{\partial p_j}$.

[39] Housing costs could rise if property taxes increase due to an increase in the 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.