Suburban Poverty: Causes and Consequences of the Changing Geography of American Poverty

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Abstract

We study whether the rise in suburban poverty disproportionately affects Black suburban residents. We build a model of segregation and Tiebout sorting that demonstrates how white residents leaving suburban areas that Black families enter can increase suburban poverty. Examining this link empirically, we construct a shift-share instrument for changes in the Black share of Northern suburbs based on population flows from the Great Migration. We find that an increase in the Black share of the suburban population causes non-black suburban poverty to increase. Investigating mechanisms, we find that wealthier incumbent residents left suburbs that Black residents entered, reducing home prices and inducing lower-income residents to move into the suburbs. Our findings provide another example of destination responses impeding Black Americans' ability to move to opportunity.

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1 Introduction

The American suburbs are changing. Since 1990, the suburban population has grown by 50%. Over the same time period, the suburbs have experienced two large-scale demographic trends. First, in a wave of Black suburbanization (Bartik and Mast 2023), we calculate that the Black suburban population doubled during this time period, mostly due to suburbanization of middle-income Black families. Second, suburban poverty has increased (Allard (2017), Kneebone and Garr (2010)), as by our calculations the suburban population under the poverty line has nearly doubled since 1990.

While middle-income Black families wanted suburban opportunities, such as improved housing conditions and amenities (Bartik and Mast 2023), American history is replete with examples of segregation and instances in which white families moved away from their Black neighbors (Rothstein 2017). Could a similar response of wealthier incumbent suburban residents have led to the increase suburban poverty?

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

We use a shift-share instrument for the racial composition of Northern suburbs to quantify this relationship from the model and to examine whether Black suburbanization caused suburban poverty to increase. We construct our instrument for changes in the Black share of Northern suburbs using the Great Migration of Black individuals from the South. This instrument uses three sources of variation. It combines the growth (shifts, or "shocks") in Black out-migration from each Southern county between 1940 and 1970 with pre-existing migrant networks (shares) that linked Southern counties to Northern cities. It also incorporates the distance between Northern suburbs and the primary Black neighborhood of each city. Taken together, these sources of variation predict our treatment, the migration of Black families to the suburbs.

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

We find that a one percentage point increase in the Black share of the suburban population causes the share of the impoverished metropolitan population that lives in the suburbs to increase by about two percentage points. It also causes the share of the impoverished non-black population that lives in the suburbs to increase by about one percentage point. That is, Black suburbanization increases suburban poverty in part by precipitating an increase in the proportion of poor non-black residents that live in the suburbs.

Our data show that this occurred because wealthier incumbent residents left suburbs that Black suburbanites entered. This reduced home prices and induced lower-income residents to move into the suburbs. Specifically, using the same instrument for Black suburbanization as above, we find significant effects of Black suburbanization on the share of wealthy residents in the suburbs and on lowest-quartile suburban home prices. We use Census microdata to analyze the movement of lower-income residents into the suburbs, and show a strong correlation between Black suburbanization and entry of lower-income residents into the suburbs.

Examining how suburban poverty can affect overall welfare, we find that the movement of poor individuals into suburban municipalities that are more dependent on property tax revenue decreases overall property tax collections. We also review research that indicates that suburban poverty decreases the ability of poor individuals to access poverty-reduction services. Further, we find that school quality, an important amenity for suburban families, decreases in suburban areas with larger increases in poverty. Finally, suburban poverty changes the distribution of welfare, as our results indicate that suburban Black families are disproportionately exposed to the increase in poverty.

Ameliorating the effects of suburban poverty requires understanding its causes. We are unaware of existing work that provides a causal explanation for the increase in suburban poverty.

Our paper also builds upon the literature studying race and neighborhood change, and in particular two main papers. First, we build on Boustan (2010) by studying long-term, racially-motivated changes in suburban neighborhoods. Boustan (2010) documents how Black migration to Northern cities led to White suburbanization. We examine racial change

[1] As we will explain in Section 4, our regression analysis takes place at the level of the shocks. Therefore, in our formal expression of the exclusion restriction, the suburban poverty variables are converted to the shock level.

in American suburbs, and document the series of events that accompanied Black migration to the suburbs: wealthier incumbent residents left, property prices fell, and poorer residents moved in. Therefore, while the existing research focuses more on the short-term demographic effects, our paper examines the longer-term population churn that occurred in the wake of the Great Migration. Specifically, though earlier work documents White flight, it does not discuss the subsequent co-movement of the poor non-black and Black populations.

Second, we relate to Derenoncourt (2022) by showing how destination responses to black in-migration diminish the gains that Black families can accrue from moving. In our case, incumbent departure increases suburban poverty, especially in suburban areas to which Black families moved. Suburban poverty is therefore another example of how destination reactions make it harder for Black Americans to "move to opportunity". The reaction of incumbent suburban residents to racial change not only increased the poverty that Black suburban residents encounter, but also increased suburban poverty more generally, as we find that Black suburbanization caused the majority of the increase in suburban poverty that we observe in our data.

Finally, this paper enriches our understanding of the spatial distribution of economic activity within metropolitan areas. Though we investigate different mechanisms, our empirical evidence supports the theoretical predictions of "the poor mov(ing) to the suburbs" from as early as LeRoy and Sonstelie (1983). More recently, the literature studying gentrification, such as Couture and Handbury (2020) and Couture, Gaubert, et al. (2024), has documented changes in the spatial distribution of income in urban areas. We do the same for suburban areas. Taken together, these papers examine how the spatial distribution of income is changing throughout the entire metropolitan area.

2 Black Suburbanization and Suburban Poverty: Data and Description

2.1 Black suburbanization

To document the increase in Black suburban residents, we first classify every census tract in the country as urban, suburban, or rural based on a map developed by the National Center for Education Statistics (NCES)[2] We the obtain data on suburban racial composition from

[2] The U.S. federal government does not officially define suburban areas. The NCES defines the suburbs as all land within Metropolitan Statistical Areas (MSAs) that is not within a principal city of the MSA and is not rural. This definition is similar to that used in Bartik and Mast (2023), though they classify 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. Therefore, we use the NCES's classifications from 2015 to form

the decennial Census (1990) and five-year ACS (2015-2019). We measure the total population as well as the Black non-Hispanic population in each suburban census tract.

We calculate that between the 1990 decennial Census and 2015-2019 ACS, the Black suburban population increased by 8.3 million, of whom the vast majority (7.1 million) are above the poverty line. Black suburbanization was largely driven by middle-class Black families searching for improved housing conditions and amenities (Bartik and Mast 2023). The authors show that improved neighborhood amenities and affordable housing prices together account for 90% of observed black suburbanization.

Of those who moved to the suburbs, Black suburbanites are primarily middle class, as "high-income Black households [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 9.1 that most Black suburban residents are middle class, though some are below the poverty line.

Though the poverty rate among black suburban residents is higher than the overall suburban poverty rate, using the 1990 decennial Census and 2015-2019 ACS we calculate in Appendix Table 9.1 that the increase in the poor Black suburban population represents only 17.6% of the total increase in the poor suburban population over this time period. Specifically, the poor suburban population increased from 7.23 to 14.19 million, while the poor Black suburban population increased from 1.32 to 2.55 million.

2.2 Suburban poverty

2.2.1 Quantifying the increase in suburban poverty

We demonstrate the increase in suburban poverty in two ways. First, we show that the poverty rate in the suburbs has increased, both absolutely and relative to urban and rural areas. Second, we show that the share of impoverished Americans who live in the suburbs has also risen. Though these broad trends have previously been identified[3], but they are largely absent from the economics literature.

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

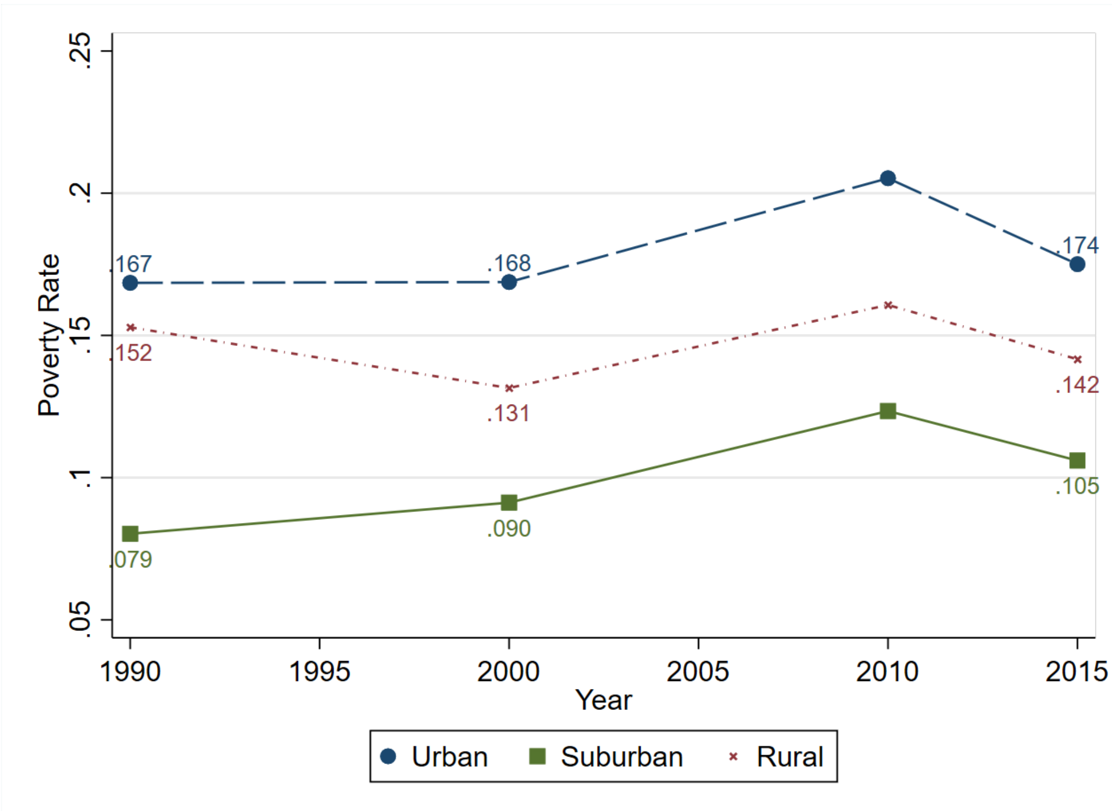
Analyzing this data, Figure 1 shows that the suburban poverty rate increased by 2.6

the suburban area of every MSA in the country.

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

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.

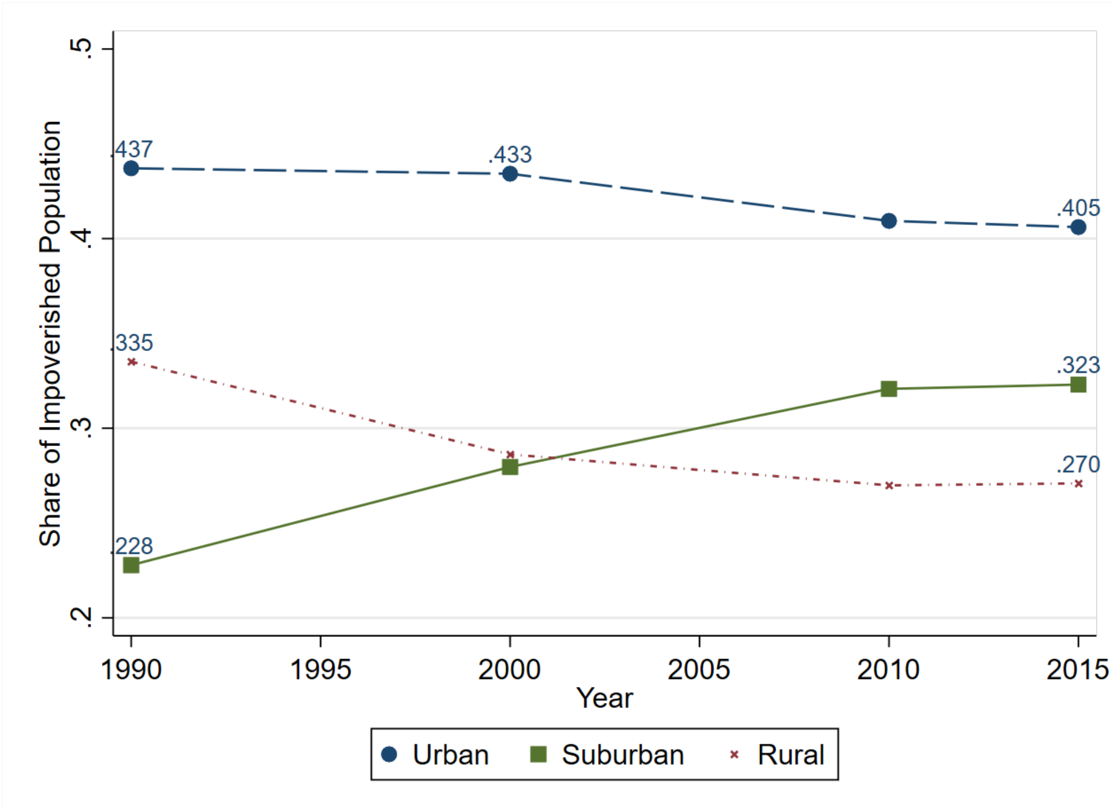
Figure 1: Poverty Rates



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

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

Figure 2: Poverty Shares



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

2.2.2 Decomposing the increase in suburban poverty

Now that we know suburban poverty is increasing, we want to know whether the increase is driven by increasing poverty among incumbent suburban residents or 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 and incumbent suburban residents. To calculate the number of people moving into and out of the suburbs, however, 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)[4].

[4]For example, we assume that the net movement of the poor population into the suburbs between 1990

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

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

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).

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.

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:

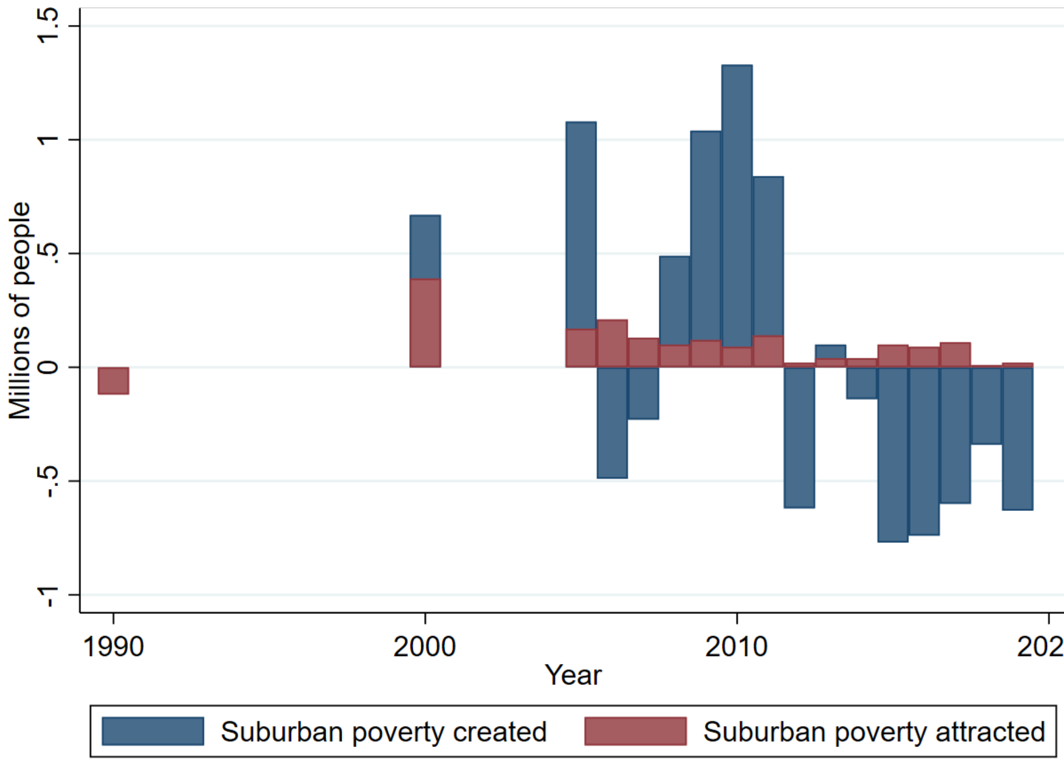
$$\begin{aligned}&\text{Suburban poverty attraction} + \text{Suburban poverty creation} = \\&(A + C - G - J) + (B + J - E - F) = \\&A + B + C - E - F - G = \\&\text{Change in number of suburban poor}\end{aligned} \tag{1}$$

We use the microdata described earlier in the section 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. Instead, we calculate poverty creation as the change in the number of individuals under the poverty line between t and $t-1$ among those who were in the suburbs in year t, and poverty attraction as the net migration into the suburbs of impoverished individuals. For consecutive years ($t-1$ and t), such as the years for which we have yearly data (2006-2019), these two terms sum to equal the change in the number of suburban poor, as in Equation 1. 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.

Calculating suburban poverty creation and attraction, we show in Figure 3 that the suburbs attracted poverty in every year except 1990, while the suburbs generally created poverty in concert with the business cycle. Between 2008 and 2011 the suburbs created more than half a million poor people every year. After 2011, suburban poverty fell every year except 2013. Nevertheless, our calculations, reflected in more detail in Table 9.3, indicate that the suburbs created poverty even during the period of relatively favorable economic conditions between 1990 and 2005[5]. Overall, since 1990 the suburbs have both created poverty and (on net) attracted impoverished individuals to move in.

[5]Recall that 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).

Figure 3: Suburban Poverty Creation and Attraction



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

2.3 Black Suburbanization and Suburban Poverty

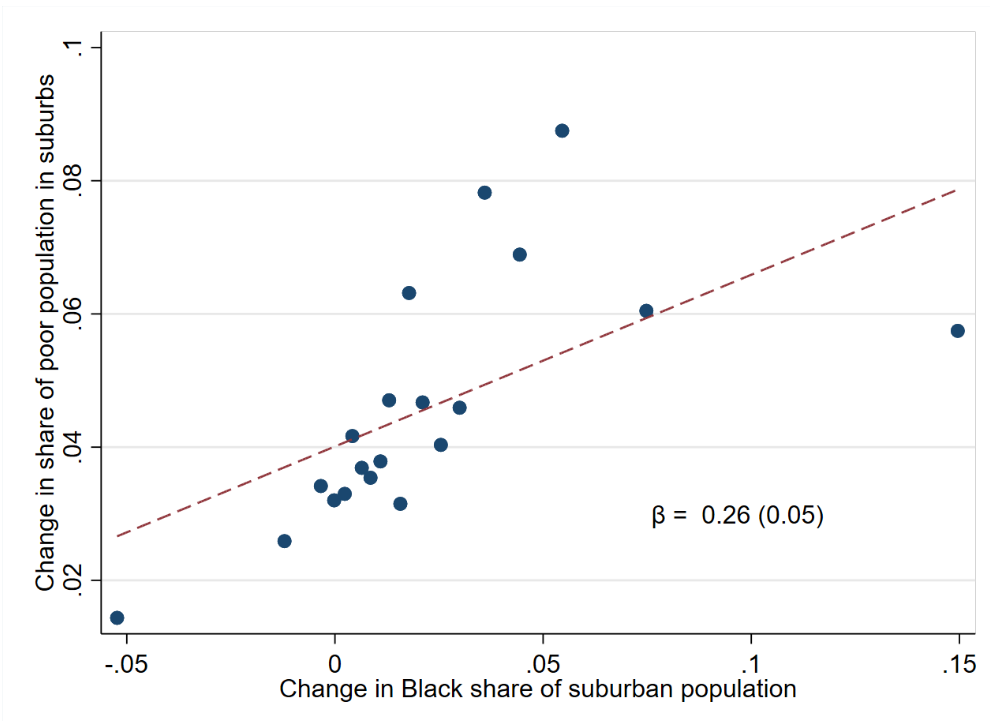
We find that the increase in suburban poverty and Black suburbanization are strongly correlated at the MSA level. Our measures of suburban poverty and Black suburbanization are calculated as changes between the 1990 decennial Census and the 2015-2019 five-year ACS. We compute the change in suburban poverty as the percentage point change in the share of an MSA's poor population that lives in the suburbs. Since the suburbs as a whole grew in population during this time period, we control for the change in the share of the MSA's total population that lives in the suburbs in our regressions. Therefore, our measure of suburban poverty captures an increase in the poor suburban population that cannot be explained by population growth alone. We compute the change in Black suburbanization as the percentage point change in the share of the suburban population that is Black.

Our summary of these variables in Appendix Table 9.2 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.

To determine the relationship between these variables, we regress the change in the share of the MSA's poor population that lives in the suburbs on the change in the Black share of the suburban population, controlling for the change in the suburbanization of the MSA's population. Our results, summarized in Figure 4, demonstrate that Black suburbanization has a statistically significant positive correlation with changes in suburban poverty (t=4.9).

Figure 4: 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, while 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.

3 Model

In this section we provide a theoretical justification for our finding in the previous section that the suburbanization of middle-class Black residents is correlated with an increase in suburban poverty. 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. To this, we add an additional jurisdiction (suburb), endogenize the quality of the public good, and alter the housing supply to be perfectly elastic instead of perfectly inelastic.

Our 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 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:

$$U_{i,r}^j(Y_i, p^j) = (Y_i - (1+t)\, p^j)^{0.75} \, (tp^j + D_r^j)^{0.25} \tag{2}$$

where Y_i is individual i's income and D_r^j reflects group-specific tastes for demographic composition. Individual income Y_i comes from a group-specific income distribution: $Y_w \sim \text{Uniform}(0, 1.1)$ and $Y_b \sim \text{Uniform}(0, 1)$. We add a property tax, at rate $t = 0.1$, where tp^j captures the quality of the public good in jurisdiction j.

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

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

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

3.2 Model results

We describe two equilibrium allocations that we obtained from simulating this model of residential choice with 1,000 individuals[6].

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 $p^{S_1} = 0.0182, p^{S_2} = 0.0182$.

Table 1: Demographic mix in first equilibrium

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

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

The average income in the suburbs is higher than in the city in this equilibrium, as evidenced in the income distribution in Figure 5. Recall that only members of group w live in the suburbs, though the poorest members of group w live in the city.

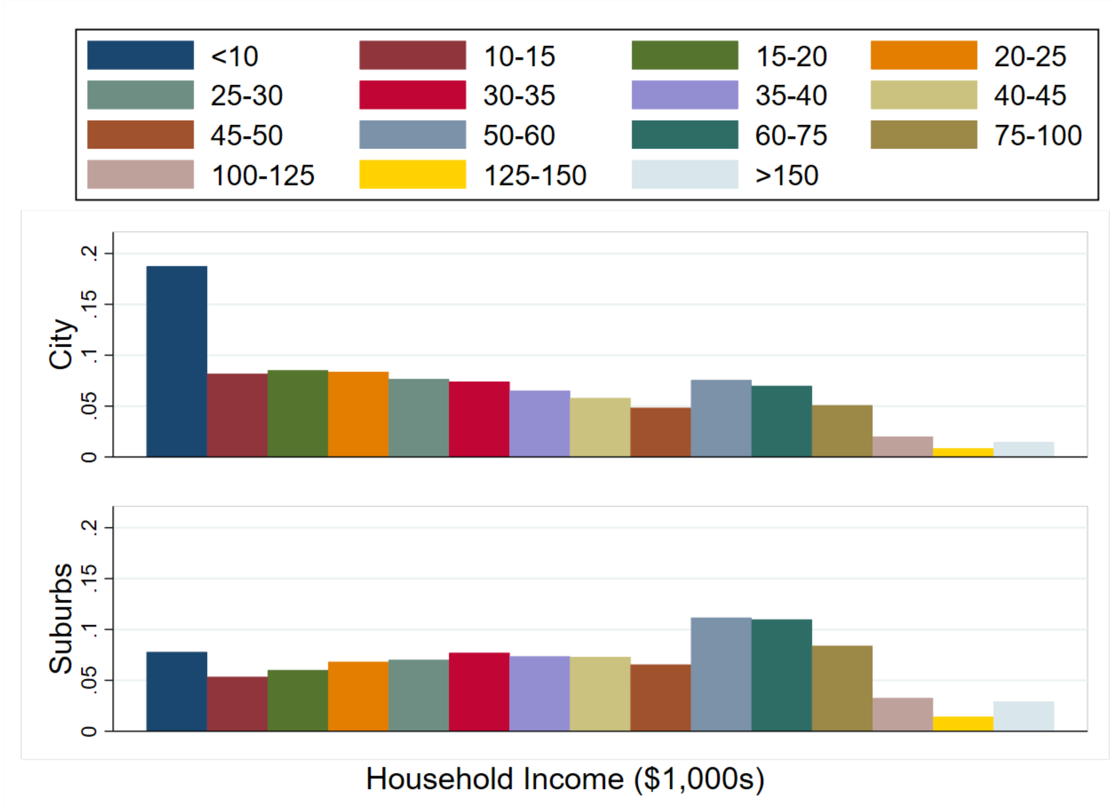
This equilibrium is reminiscent of the structure of American metropolitan areas before the Fair Housing Act. Though in this model members of group b chose to live in the city, historically Black families faced pressure to live in cities while wealthier White families lived in segregated suburbs (Rothstein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

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

Figure 5: Income distribution in the first equilibrium (model)

We compare the income distribution from the model with the empirical income distribution of Chicago's urban and suburban areas from the 1990 Decennial Census. The data for this exercise is discussed in more detail in Section 2. Examining the empirical income distribution, we find that there is a higher frequency of lower income individuals in the city than in the suburbs, while there is a higher frequency of higher-income individuals in the suburbs than in the city. The model and empirical results are consistent in this regard. However, the model features more extreme income segregation across areas than does the empirical income distribution.

Figure 6: Annual income in Chicago metropolitan area, 1990 decennial Census



Note: Household income data aggregated from the 1990 decennial Census for all urban and suburban census tracts in the Chicago metropolitan area.

3.2.2 Equilibrium two: integrated suburbs

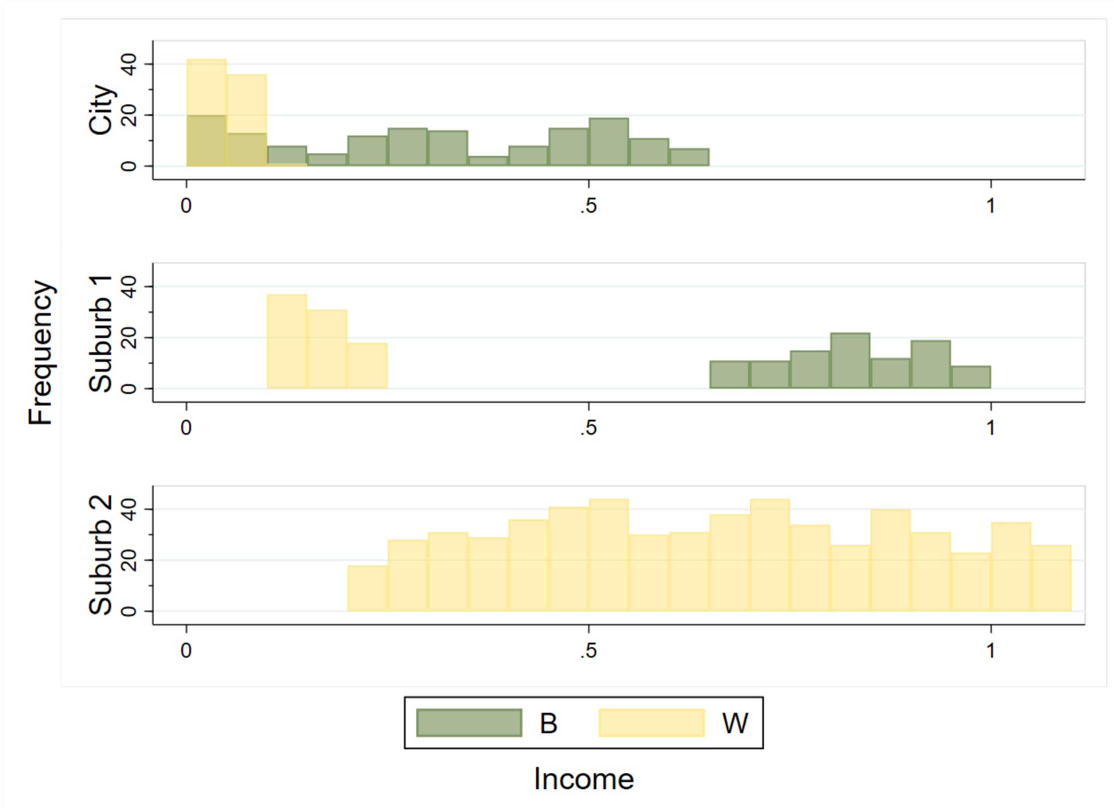
In the second equilibrium, the suburbs are more integrated along demographic lines but are stratified by income. Housing prices that support this equilibrium are $p^{S_1} = 0.005, p^{S_2} = 0.0176$.

Table 2: Demographic mix in second equilibrium

r	City	Suburb 1	Suburb 2
w	70	96	584
b	141	109	0

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

Figure 7: Income distribution in the second equilibrium (model)



A contingent of poor residents, who have income below 0.3, now lives in the suburbs (specifically, the first suburb) in this equilibrium. In contrast, the minimum suburban income was approximately 0.4 in the first equilibrium. 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. Figure 7 presents the bimodal distribution of income in suburb one, and the more uniform (though censored) distribution of income in suburb two, in this equilibrium.

In the second suburb, higher housing prices deter the poorest residents. However, some individuals with incomes between 0.2 and 0.4 live in this suburb. All residents of this suburb, including these poorer residents, are members of group w.

We then compare these model predictions with the income distribution in Chicago from the 2015-2019 five-year American Community Survey (ACS). We classify "poor suburbs" as census tracts with a poverty rate of 5% or higher and all other suburban tracts as "rich suburbs". We once 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, as does the bimodal distribution of wealth in the poorer suburb. Unlike in the model, though, there are wealthier individuals who live in the city.

Figure 8: Annual income in Chicago metropolitan area, 2015-2019 ACS

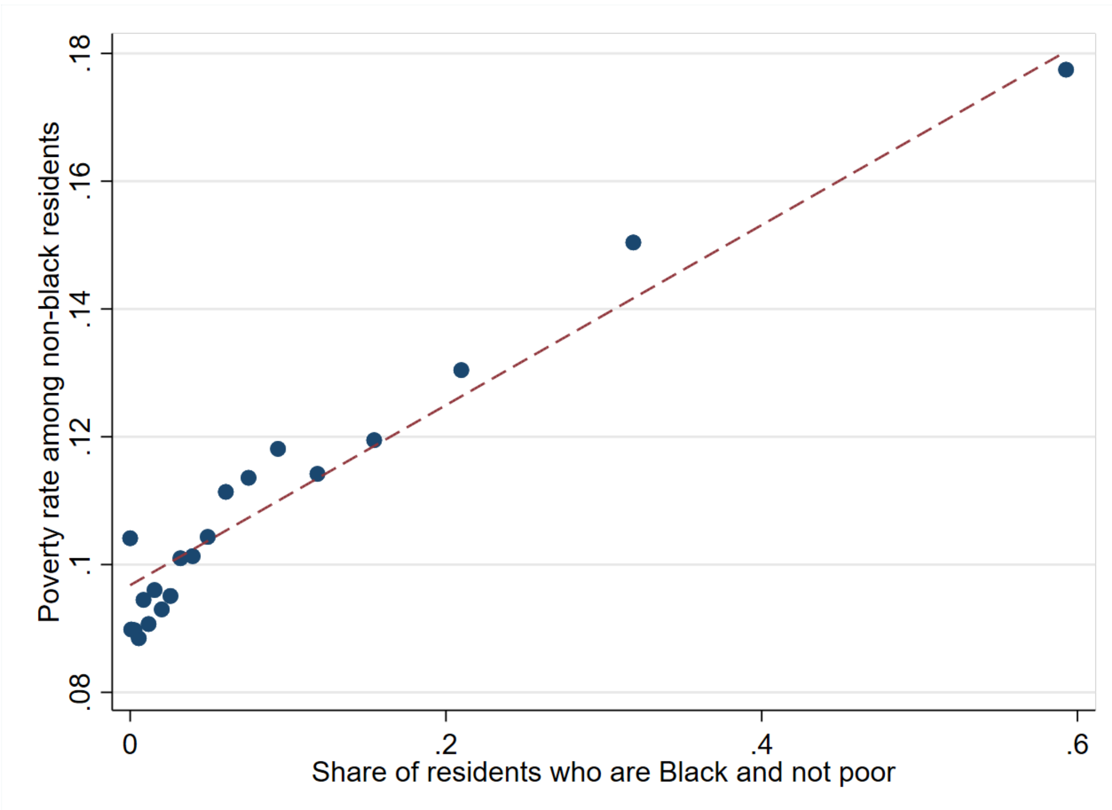
Note: Household income data aggregated from the 2015-2019 five-year ACS for all urban and suburban census tracts in the Chicago metropolitan area.

3.3 Implications

The results of this simple model demonstrate how suburbanization of group b can increase suburban poverty, even among group w and even if the overall poverty rate remains constant, when an event such as the migration of members of group b to the suburbs leads to a new equilibrium. In the second equilibrium, wealthier residents of group b live in suburb one. Since members of group w do not prefer this demographic composition, housing prices are low in suburb one in this equilibrium. This affordability leads some of the poorest members of group w to choose to live there. Taken together, these theoretical results indicate that demographically-influenced movement of the white suburban population between jurisdictions and changes in housing prices may be important mechanisms by which Black suburbanization increases suburban poverty.

This model implies that wealthier Black residents live in the same suburban areas as poorer non-black residents, which is evidence in American suburbs in the 2015-2019 ACS. As shown in Figure 9, our census tract-level data shows that the poverty rate among non-black suburban residents increases with the share of the tract population that is non-impoverished Black residents.

Figure 9: Poor non-black residents live with non-poor Black residents in the suburbs



Note: Poverty and race data come from 2015-2019 five-year ACS tract-level estimates. Data from 27,084 suburban census tracts are included in this figure.

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

Though we now know that there is a theoretical rationale for a relationship between the suburbanization of middle-class Blacks residents and suburban poverty, we do not know the magnitude of the relationship. Since the model involves stratification by race and income, it delivers predictions in which small movements of one group can lead to large responses of another group. Knowing the empirical size of this relationship tells us how much poverty we expect to follow middle-class Black residents to the suburbs.

4 Empirical Strategy

We now want to determine the magnitude of the relationship between Black suburbanization and suburban poverty described above. That is, we want to estimate β in the causal model of equation 3. In this equation, y_i is the share of the impoverished population of MSA i that lives in the suburbs and x_i is the Black share of the suburban population of MSA i. We will later examine additional outcomes, denoted $\tilde{y}_i$, such as the share of the impoverished non-black population of MSA i that lives in the suburbs.

$$\Delta_{1990,2015}\, y_i = \alpha + \beta \Delta_{1990,2015}\, x_i + \varepsilon_i \tag{3}$$

If $\Delta_{1990,2015}\, x_i$ and ε_i are not orthogonal, then estimating β using OLS will not reveal the true causal relationship. For example, if Black residents moved to suburbs that were already becoming poorer, this reverse causality would bias the OLS estimate of β. Alternatively, if some characteristic of the suburbs, such as the growth of affordable housing, is correlated with both x_i and y_i but not included in the regression, then this omitted variable would also bias the OLS estimate of β.

To address these endogeneity concerns and estimate the causal relationship, we develop a shift-share instrument for the change in the Black share of the suburban population between 1990 and 2015-2019. As in Boustan (2010), Derenoncourt (2022), and Cui (2024), our shift-share instrument uses variation induced by the Great Migration of Black individuals to Northern cities between 1940 and 1970. We build on these existing empirical strategies by incorporating the distance from the predominant urban Black neighborhood to the nearest suburb into our instrument. Validity of this instrument relies on exogeneity of the shocks - that shocks to the Southern counties that Black individuals left between 1940 and 1970 are unrelated to unobserved determinants of changes in contemporary Northern suburban poverty.

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

$$\Delta_{1990,2015}\, y_i = \alpha + \beta\Delta_{1990,2015}\, x_i + \gamma\mathbf{c_i} + \epsilon_i \tag{4}$$

4.1 Constructing our shift-share instrument

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

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

$$z_i = \sum_k e_i s_{ik} g_k \tag{5}$$

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

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

$$s_{ik} = \frac{\text{Number of Black migrants from } k \text{ to } i \text{ between 1935 and 1940}}{\text{Total number of Black migrants to } i \text{ between 1935 and 1940}} \tag{6}$$

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:

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

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

$$\text{Predicted Black net out-migration rate}_{kt} = \hat{\alpha} + \hat{\beta} X_{kt} \tag{8}$$

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 8, divided by the number of Black migrants leaving from k between 1935 and 1940. That is,

$$g_k = \frac{\text{Predicted number of Black net out-migrants from } k \text{ between 1940 and 1970}}{\text{Number of Black out-migrants from } k \text{ between 1935 and 1940}} \tag{9}$$

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

Table 3: 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, from Boustan 2016. The increase in the suburban Black share is measured between the 1990 decennial Census and 2015-2019 ACS.

To strengthen our instrument, we use a regression weight e_i that measures the inverse of the distance to the suburbs. We use this weight because, all else equal, we expect MSAs in which the suburbs are closer to the predominant urban Black neighborhood to have a bigger increase in the Black suburban population because Black suburban residents tend to live close to existing urban Black settlements (Wiese 2019). For each MSA i, we measure the distance d_i from the center of the largest urban Black neighborhood to the nearest suburb. We describe how we measure this distance in more detail in Appendix 9.4. Our regression weight is then $e_i = d_i^{-1}$.

4.2 Instrument Validity

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

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

We write the exclusion restriction at the level of the shocks, because our estimating equation is the shock-level regression equation 12 described below. Our exclusion restriction, equation 10, means that county-level migration shocks g_k must be orthogonal to MSA-level unobservables[7]. 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.

$$\mathbb{E}\left[\sum_k g_k\, s_k \tilde{\varepsilon}_k\right] = 0 \tag{10}$$

Though we cannot explicitly test the exclusion restriction, we conduct a pre-trends test, as recommended by Borusyak et al. (2022), in which we replace our main outcome variable with the outcome for the period prior to our analysis[8]. We run the shock-level equivalent of equation 11 (which is written at the MSA level for ease of interpretation), instrumenting for x_i with z_i. A statistically significant coefficient δ would indicate that our instrument is correlated with an unobserved confounding variable, violating the exclusion restriction.

$$\Delta_{1980,1990}\, y_i = \alpha + \delta \Delta_{1990,2015}\, x_i + \gamma \mathbf{c_i} + \varepsilon_i \tag{11}$$

The results of the pre-trends test support the validity of our instrument for black suburbanization. In column (2) we control for MSA population in 1990 and Census Region fixed effects, following Boustan (2010). Regardless of whether we include these control variables, the estimates of δ in Table 4 are not statistically significant. In addition to lacking statistical significance, these coefficients are also approximately one order of magnitude smaller than

[7]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).

[8]We use 1980 as the starting point due to data availability. We cannot use 1970 or earlier because there were large suburban areas that were not yet included in tract-level Census data.

in our main results.[9]

Table 4: Pre-trends test

	Change in suburban poverty 1980-1990	
	(1)	(2)
Change in suburban Black share	-0.163	-0.215
	(0.195)	(0.332)
Observations	1174	1174
Control Variables	No	Yes

Note: The unit of observation is a Southern county, which is the level at which our robust standard errors are clustered. The dependent variable is the change in the share of the poor population of the MSA that lives in the suburbs between 1980 and 1990. The independent variable is the change in the suburban black share between 1990 and 2015. Control variables at the MSA level are total population in 1990 and Census Region fixed effects.

Second, Borusyak et al. (2022) suggest estimating shift-share coefficients at the level of the shocks to obtain correct standard errors[10]. We follow their suggestion with our sample of 1,174 Southern counties[11], as described below. Therefore, the unit of observation in our regressions are Southern counties that sent black migrants to Northern MSAs. There are 97 Northern MSAs represented in this sample.

To estimate the shock-level regression, we must convert our MSA-level measures of changes in suburban poverty and Black suburbanization from equation 3 to the level of the shocks[12]. 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:

$$\bar{y}_k^{\perp} = \alpha + \beta \bar{x}_k^{\perp} + \bar{\varepsilon}_k^{\perp} \tag{12}$$

[9]Borusyak et al. (2022) also suggest testing the control variables for balance by using them as the dependent variables in equation 11. Doing so, we detect imbalance in our West and Midwest Census Region dummies. However, the authors note that one can assess whether this imbalance may lead to bias by determining whether the coefficients are robust to including these controls. As we will see, the qualitative interpretation of our coefficients is not sensitive to the inclusion of these controls.

[10]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.

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

[12]In practice, we use the Stata program *ssaggregate* to do so convert 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.

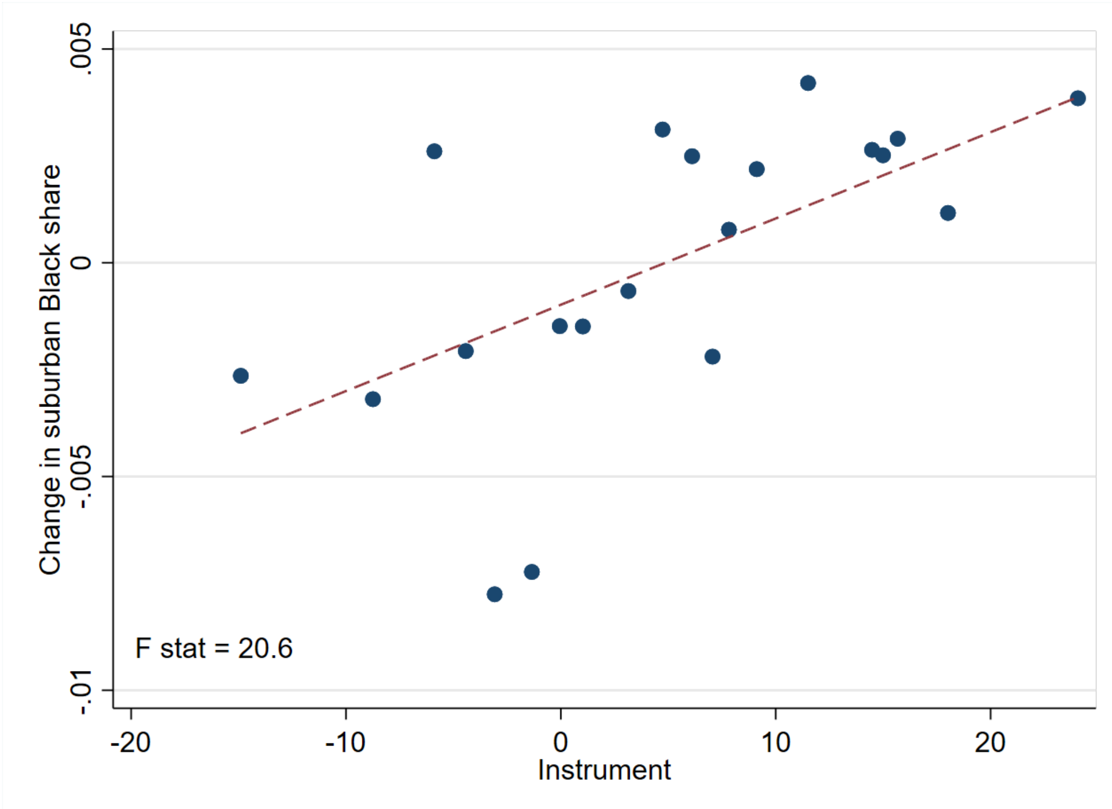
Though we obtain our results from estimating the shock-level equation 12, the point estimate of β is equivalent to that from an MSA-level regression (Borusyak et al. 2022). Therefore, our estimates of β can be interpreted at the MSA level, and reflect the magnitude of the increase in suburban poverty resulting from a one percentage point increase in the Black share of the suburban population.

Finally, Borusyak et al. (2022) note that if the sum of weighted exposure shares $\sum_k e_i s_{ik}$ is not constant across locations i, one must control for the sum of these shares in the regression. Therefore, we control for the sum of exposure shares, $\sum_k e_i s_{ik} = \sum_k s_{ik}/d_i$, in our regressions. 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 below, our instrument z_i can indeed predict changes in Black suburbanization between 1990 and 2015-2019. Figure 10 is a shock-level binscatter of the change in the Black share of the suburban population between 1990 and 2015-2019 against our instrument. Our instrument has a positive and statistically significant relationship with Black suburbanization. F-statistics for each specification are included in our main table of results.

Figure 10: First stage on Black suburbanization



Note: Observations at the shock (Southern county) level, of which there are 1,174. The dependent variable here 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.

5 Results

Using the shift-share instrument described above, we find that increases in the Black share of the suburban population caused statistically significant increases in both overall suburban poverty and non-black suburban poverty. The magnitude of the coefficients implies that Black suburbanization caused most of the increase in suburban poverty in our data.

In Table 5 we display our results from estimating equation 12, a shock-level IV regression of the change in suburban poverty on the change in the Black share of the suburban population. We control for the sum of exposure shares in each specification. Though the coefficients vary depending on which instrument we use and whether we control for the MSA's population and Census Region, they remain positive and statistically significant throughout. In columns one and two, we set $e_i = 1$ and use the instrument that does not account for the distance to the suburbs. When we include the suburban distance regression weighting $e_i = d_i^{-1}$ in column three, the F-statistic increases to 18.8. Including the MSA-level control variables in column four changes the coefficient slightly, as does weighting each MSA by population in column five.

Table 5: Main Results: Black suburbanization and suburban poverty

	Change in suburban poverty 1990-2015				
	(1)	(2)	(3)	(4)	(5)
Change in suburban Black share	2.329***	3.371***	1.795***	2.345***	3.657***
	(0.355)	(0.612)	(0.316)	(0.494)	(1.079)
Observations	1174	1174	1174	1174	1174
Control Variables	No	Yes	No	Yes	Yes
Suburban Distance Weighting	No	No	Yes	Yes	Yes
Population Weighting	No	No	No	No	Yes
Effective F-statistic for IV	12.9	16.6	18.8	20.6	10.2

Note: The unit of observation is a Southern county, which is the level at which our robust standard errors are clustered. The dependent variable is the change in the share of the poor population of the MSA that lives in the suburbs. The independent variable is the change in the suburban Black share between 1990 and 2015. Control variables at the MSA level are total population in 1990 and Census Region fixed effects. Regressions weights in column five are based on MSA population in 1990.

Given the units, the interpretation of these coefficients is that a one percentage point increase in the Black share of the suburban population caused the share of the total impoverished metropolitan population that lives in the suburbs to increase by approximately two percentage points (2.3 percentage points in our preferred specification in column four).[13]

The magnitude of these IV coefficients indicates that the increase in the Black share of the suburban population caused most of the increase in suburban poverty observed in our data. These coefficients imply that a 2.2 percentage point increase in the Black share of the suburban population (the mean increase across MSAs in our sample) caused an increase in the share of the metropolitan-area poor population that lives in the suburbs of approximately 5.1 percentage points. The mean increase in the share of the metropolitan-area poor population that lives in the suburbs in this sample is 6.5 percentage points, so our results imply that the increase in the suburban Black share caused approximately $\frac{3}{4}$ of the increase in suburban poverty.

While our results imply that Black suburbanization caused most of the increase in suburban poverty, we note that most of the increase in suburban poverty has been among the

[13]These coefficients remain significant if we cluster our standard errors at the state level.

non-black population. As mentioned previously, our data indicates that the increase in the impoverished Black suburban population constitutes 17.6% of the total increase in the impoverished suburban population. Since our results indicate that the increase in the suburban Black share caused $\frac{3}{4}$ of the increase in suburban poverty, then the increase in the suburban Black share must have caused an increase in non-black suburban poverty.

We next examine the effects of Black suburbanization on non-black suburban poverty, and find that Black suburbanization caused non-black suburban poverty to increase. To estimate these regressions, we replace y_i from the our main regressions with $\tilde{y}_i$, measuring suburban poverty among the non-black suburban population. The coefficients in Table 6 are approximately half the size of the coefficients in Table 5, but remain statistically significant. Our results show that a one percentage point increase in the Black share of the suburban population caused the share of the poor non-black population that lives in the suburbs to increase by approximately one percentage point. These results indicate that Black suburbanization increased suburban poverty through its effect on both the Black and non-black populations. Further, these results indicate that, on average, Black families moved into suburbs in which 2.2 percent more of the non-black metropolitan poor population lived than they would have if there was no relationship between suburban Black share and suburban poverty.

Table 6: Black suburbanization and non-black suburban poverty

	Change in non-black suburban poverty 1990-2015				
	(1)	(2)	(3)	(4)	(5)
Change in suburban black share	1.629***	2.311***	0.982***	1.285***	1.731*
	(0.313)	(0.594)	(0.285)	(0.459)	(1.007)
Observations	1174	1174	1174	1174	1174
Control Variables	No	Yes	No	Yes	Yes
Suburban Distance Weighting	No	No	Yes	Yes	Yes
Population Weighting	No	No	No	No	Yes
Effective F-statistic for IV	11.6	14.6	17.7	20.1	7.8

Note: The unit of observation is a Southern county, which is the level at which the robust standard errors are clustered. The dependent variable is the change in the share of the poor non-black population of the MSA that lives in the suburbs. The independent variable is the change in the suburban Black share between 1990 and 2015. Control variables at the MSA level are total population in 1990 and Census Region fixed effects. Regressions weights in column five are based on MSA population in 1990.

Finally, we note that the IV coefficients are consistently larger than the OLS coefficients. The relevant coefficients using OLS are 1.21 for column four of Table 5 and 0.60 for column four of Table 6. These OLS coefficients are approximately half of the size of the corresponding IV coefficients, indicating that omitted variables bias shrank the OLS coefficients towards zero. One explanation for this downward bias is that Black suburbanites endogenously choose suburbs that subsequently experienced relatively smaller increases in poverty.

6 Mechanisms: Suburban Demographic Change

We now investigate the mechanisms by which Black suburbanization increased suburban poverty. Our model demonstrated how demographic tastes, changes in home prices, and the relocation of poorer individuals between the city and suburbs can link Black suburbanization to suburban poverty. In this section, we empirically examine these mechanisms and chronicle the resulting change in suburban demographics.

6.1 Wealthier residents depart

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

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

Our results in Table 7 indicate that Black suburbanization causes the proportion of the non-poor metropolitan population that lives in the suburbs to decline. The independent and dependent variables in this regression are both shares, so the magnitude of the coefficient in column four implies that a one percentage point increase in the Black share of the suburbs caused the share of the non-poor population that lives in the suburbs to decrease by 0.259 percentage points. These results indicate that wealthier suburban residents left the suburbs as Black residents moved in.

Table 7: Black suburbanization and wealthy suburbanites

	Change in suburban non-poor 1990-2015				
	(1)	(2)	(3)	(4)	(5)
Change in suburban black share	-0.246***	-0.360***	-0.176***	-0.259***	-0.359***
	(0.064)	(0.092)	(0.061)	(0.068)	(0.115)
Observations	1174	1174	1174	1174	1174
Control Variables	No	Yes	No	Yes	Yes
Suburban Distance Weighting	No	No	Yes	Yes	Yes
Population Weighting	No	No	No	No	Yes
Effective F-statistic for IV	12.9	16.6	18.8	20.6	10.2

Note: The unit of observation is a Southern county, which is the level at which our robust standard errors are clustered. The dependent variable is the change in the share of the non-poor population of the MSA that lives in the suburbs. The independent variable is the change in the suburban Black share between 1990 and 2015. Control variables at the MSA level are total population in 1990 and Census Region fixed effects.

6.2 Affordable homes decrease in price

As the share of the non-poor population that lives in the suburbs declines, demand for suburban housing and home prices may decline as well. Given our focus on the movement of impoverished families into the suburbs, we focus on changes in the bottom quartile of the home price distribution.

In this analysis, our dependent variable $\tilde{y}$ is the percent change between 1990 and 2015-2019 in the 25^{th} percentile of the suburban home price distribution. Our data for this analysis comes from the 1990 decennial census and 2015-2019 ACS. For each MSA, we use tract-level median home prices to compute the value at the 25^{th} percentile of the suburban home price distribution. $\tilde{y}_i$ is then the percent change in this value between 1990 and 2015-2019. We estimate equation3 the same way as in the previous subsection, but with this new $\tilde{y}$.

Table 8: Black suburbanization and suburban home prices (25th percentile)

	Growth in 25th percentile of suburban home prices 1990-2015				
	(1)	(2)	(3)	(4)	(5)
Change in suburban black share	-19.699***	-19.624**	-19.539***	-13.780**	-17.637
	(6.458)	(8.560)	(5.122)	(5.651)	(15.722)
Observations	1174	1174	1174	1174	1174
Control Variables	No	Yes	No	Yes	Yes
Suburban Distance Weighting	No	No	Yes	Yes	Yes
Population Weighting	No	No	No	No	Yes
Effective F-statistic for IV	11.6	12.3	17.7	19.2	5.6

Note: The unit of observation is a Southern county, which is the level at which our robust standard errors are clustered. The dependent variable is the percent growth in home prices at the 25th percentile of the suburban home price distribution for each MSA. The independent variable is the change in the suburban Black share between 1990 and 2015. Control variables at the MSA level are total population in 1990 and Census Region fixed effects.

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

6.3 Entry of lower-income residents

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

Unlike in the previous two subsections, here we need to separate incumbent suburban residents from individuals who moved into the suburbs from elsewhere. Census microdata can distinguish movers from incumbent residents, but the finest level of geography at which this data is publicly available is the Public Use Microdata Area (PUMA)[14]. Unfortunately, these coarse geographic units prevent us from distinguishing between suburban and urban

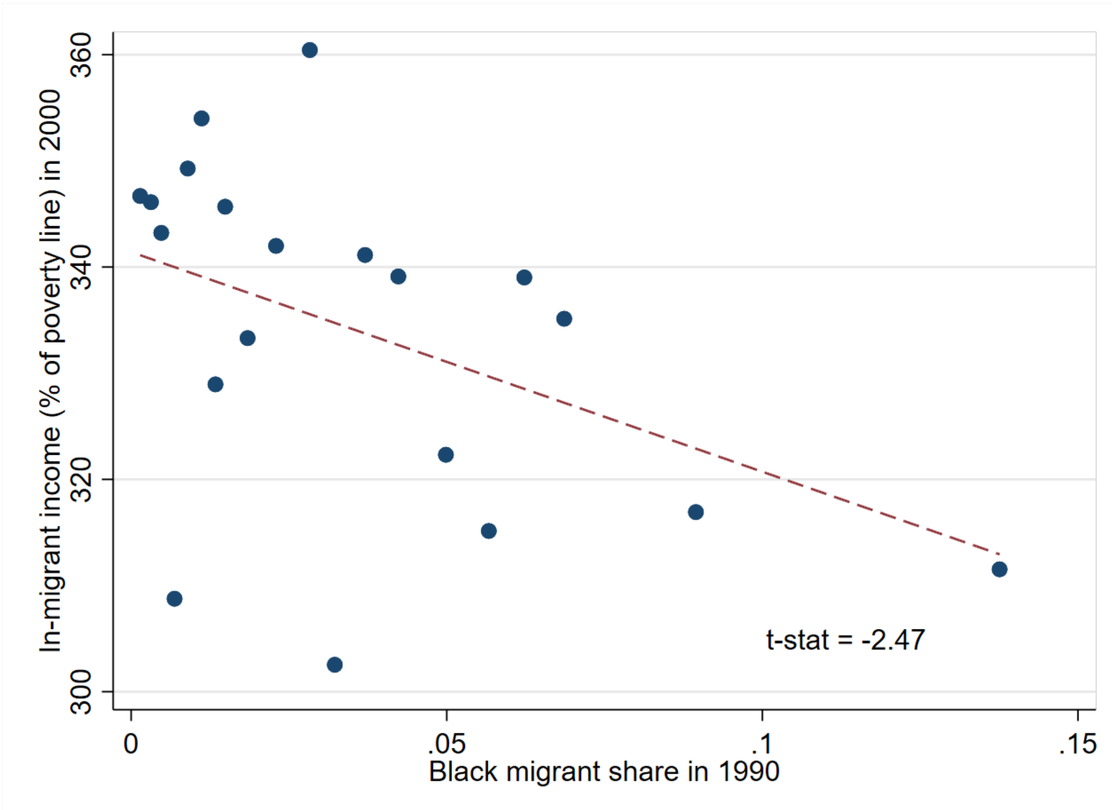
[14] PUMAs are designed to include at least 100,000 residents. Our previous analysis classified, and then aggregated, census tracts, which are designed to have approximately 4,000 residents.

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, and since we have not yet developed a PUMA-level instrument, the following analysis is correlational instead of causal.

However, we do find a correlation between Black in-migration and subsequent in-migration of impoverished individuals when analyzing suburban PUMAs[15]. We use Census and ACS microdata to create our dependent variable, which is the average income of individuals who moved into suburban PUMAs between 1995 and 2000. Our independent variable is then the share of residents of each suburban PUMA who were black in-migrants in 1990. As the binscatter in Figure 11 indicates, there is a negative relationship between these two variables: the average income of individuals who moved into suburban PUMAs decreased as the Black migrant share of the PUMA increased. Although this relationship may not be causal, it suggests that poorer individuals followed Black residents into the suburbs.

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

Figure 11: 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, for suburban CONSPUMAs, the income (expressed as a percentage of the poverty line) of new suburban residents in 2000 declines as the share of CONSPUMA residents in 1990 who are new Black residents increases.

Taken together, the evidence presented in this section demonstrates that Black suburbanization causes suburban poverty to increase because it leads suburban residents who are not poor to leave the suburbs, increases the affordability of suburban housing, and facilitates the movement of lower-income residents into the suburbs.

7 Consequences of Suburban Poverty

In this section we examine the consequences of suburban poverty and briefly describe potential policy responses. Broadly, suburban poverty could change aggregate welfare or the distribution of welfare. We first focus on the effects that the changing spatial distribution of poverty could have for the the distribution of welfare, and then for aggregate welfare.

7.1 Distribution of Welfare

The increase in suburban poverty can effect the distribution of welfare if certain groups are disproportionately exposed to the rise in poverty. From our findings in Section 5, we know that suburban poverty has increased more in suburban areas that have more Black suburbanization.

Specifically, our estimates of β in Table 6 indicate that Black suburban residents in the average metropolitan area live in suburbs in which the share of the non-black poor metropolitan population that lives in the suburbs is approximately 2.2 percentage points higher. That is, the mechanisms discussed in Section 6 by which Black suburbanization increases suburban poverty expose Black suburban residents to a disproportionate amount of the increase in suburban poverty.

Given our estimates of β, Black suburban residents are exposed to more poverty than if incumbent residents had had less of a reaction to Black families entering the suburbs. Our analysis of the 2015-2019 ACS indicates that the poverty rate among non-black residents that live in the same census tract as the average non-poor Black suburban resident is almost 1.5 times higher than for the average non-poor White suburban resident. Given that living in a lower-poverty neighborhood provides many benefits to children (Chetty et al. 2016), the increase in suburban poverty may not only affect the welfare of Black suburban adults, but also their children.

7.2 Aggregate welfare

We argue that keeping the amount of poverty constant, but redistributing poor individuals across space, can affect aggregate welfare. First, impoverished individuals are harmed if the accessibility of poverty reduction services declines. Second, total local property tax revenues may fall if impoverished individuals depress home prices in areas that are particularly dependent on revenue from property taxes.

7.2.1 Mismatch between location of poverty and services

Many services designed to aide those in poverty are provided at the local level. We assume, all else equal, that it is optimal for impoverished people to live in areas where they can access these services. However, the increase in suburban poverty means many poor individuals have moved away from the urban centers where these services are best provided.

Allard and Pelletier (2021) summarize research into the mismatch between the location of impoverished individuals and high-quality anti-poverty services:

“Apart from a core set of federal public cash and in-kind assistance programs, 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. Non-profit human service programs for low-income households receive roughly $100 billion in public and private charitable support each year, comparable to annual spending on key federal programs” like SNAP and the Earned Income Tax Credit. However, unlike the federal programs, the quality and availability of nonprofit services vary widely across space. Therefore, accessibility to quality programs depend on where one lives.

Suburbs face several challenges in sustaining high-quality provision of these services. Initial federal investments in nonprofit human service programs in the 1960s and 1970s focused on urban centers, providing them with more experience and a longer period of institutional knowledge. Additionally, poverty in the suburbs is spread across larger areas, limiting economies of scale in service provision. Finally, since the suburbs are made up of multiple municipalities, any one suburban municipality may be discouraged from developing anti-poverty programs due to political economy considerations (Allard 2017).

Indeed, the gap between resources and need is particularly acute in the suburbs, as more than two-thirds of all nonprofit human services expenditures occur in urban areas (Allard and Pelletier 2021). The difference in expenditure between urban and suburban areas has only increased, as the authors find that expenditure growth was higher in urban than suburban counties between 2000 and 2017, even as suburban poverty expanded during this period.

This gap in resources translates into a gap in service quality, as documented by Allard and Pelletier (2023), who “find evidence that nonprofit health and human service provision per poor resident is less robust in suburban areas, and especially in those experiencing high rates of poverty or areas with a relatively higher share of Black residents.”

Though we believe that the mismatch that suburban poverty generates between where poverty reduction services are best provided and where they are needed reduces aggregate welfare, we are unaware of causal evidence relating residential location to poverty duration. This remains an important area for future research.

7.2.2 Financing of local public goods

In addition to a mismatch between where poverty reduction programs are provided and where people need them, the geographic distribution of poverty could affect the total amount of revenue local governments can raise. Suburban municipalities are sensitive to decreases in property values because most municipal tax revenue comes from property taxes, and local governments generally have to balance their budgets (Glaeser 2013). Therefore, public good provision could suffer if poor individuals move to municipalities that are more dependent on property tax revenue and depress property values there.

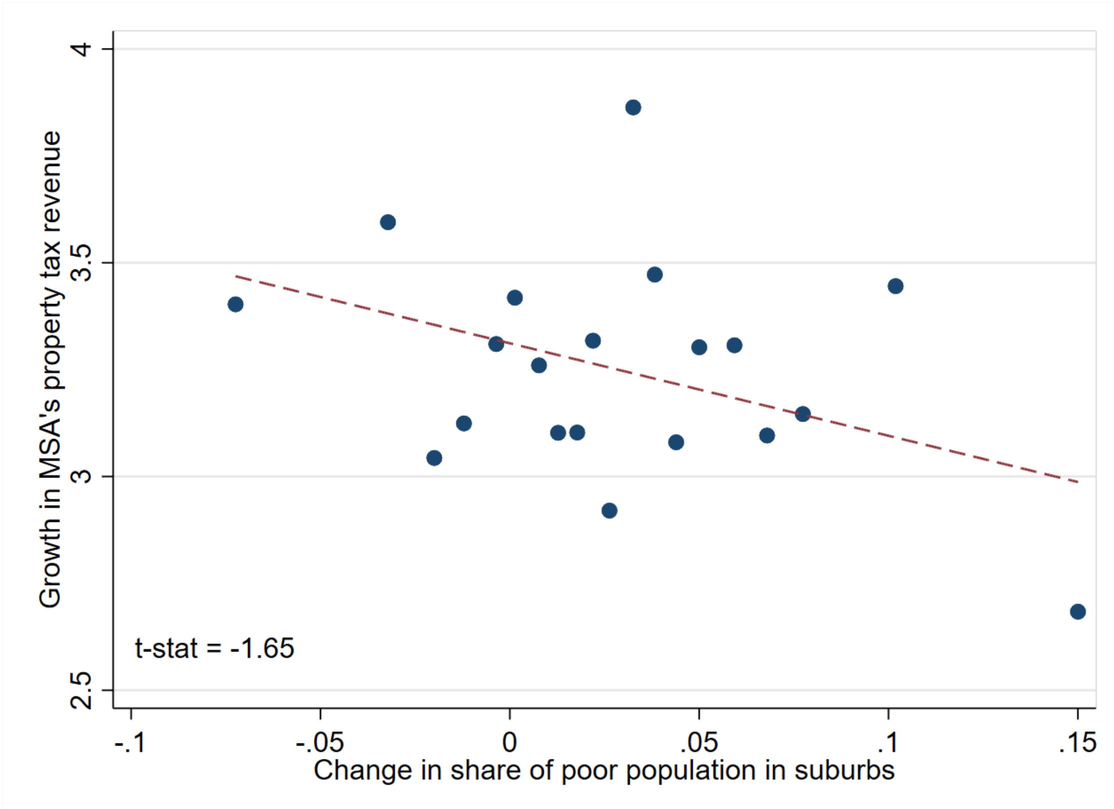
To examine these predictions empirically, we analyze the correlation between suburban poverty and property tax collections. We use Census data on municipal finances as provided by Williamette University (Pierson et al. 2015). We overlay census tracts onto Census places to classify municipalities as urban, suburban, or rural. We aggregate the suburban municipalities of a given MSA together, and examine growth in property tax collections from those municipalities between 1992 and 2017 against the increase in the share of the MSA's poor population that lives in the suburbs. We control for the change in the share of the MSA's population that lives in the suburbs. We find a statistically significant negative relationship (t=-3.5), displayed in Appendix Figure 9.3, indicating that suburban poverty decreases the ability of suburban municipalities to garner revenue from property taxes.

We then analyze property tax receipts for the entire MSA. Our independent variable, the change in suburban poverty between 1990 and 2015, remains the same. In this regression, we control for the growth in the MSA's population[16]. We find that suburban poverty decreases growth in the MSA's total property tax receipts, though this effect is only marginally statistically significant at the 10% level. Nevertheless, this analysis suggests that some non-linearities in the property tax regime means that changes in the geographical distribution of poverty affects the overall amount of revenue generated from property taxes.

Though we do not claim that these relationships are necessarily causal, we believe that this evidence suggests that there is a relationship between the geographic distribution of poverty and aggregate property tax revenue.

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

Figure 12: Property tax revenue (MSA) and suburban poverty



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

7.2.3 Public good quality and effects on homeowners

If tax revenue is spent efficiently on public goods, then the decrease in tax revenue documented above directly decreases the quality of public goods. We now directly examine the quality of public goods provided by local governments. We note that decreases in public good quality may be especially costly for homeowners.

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

$$V_{ij} = (Y_i - p_j)B_j\epsilon_{ij} \tag{13}$$

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 look more like:

$$V'_{ij} = (Y_i + \frac{p_j}{\kappa})B_j\epsilon_{ij} \tag{14}$$

Here, $\frac{\partial V'}{\partial p_j} > 0$ for someone who owns a home in j, since changes in p_j do not affect their payment for housing and 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 $\frac{dV'}{\partial p_j} > \frac{dV}{\partial p_j}$.

In this section we analyze use the quality of local schools as a measure of local public good or amenity quality, and analyze how it responds to changes in suburban poverty. This amenity is especially important for homeowners because it is more difficult for homeowners to move locations if school quality changes. To measure school quality, we use data from NCES on the high school completion rate of school districts[17] from 1991 through 1997. We then obtain school district cohort graduation rates from 2015 through 2018 from the Department of Education's Ed Data Express.

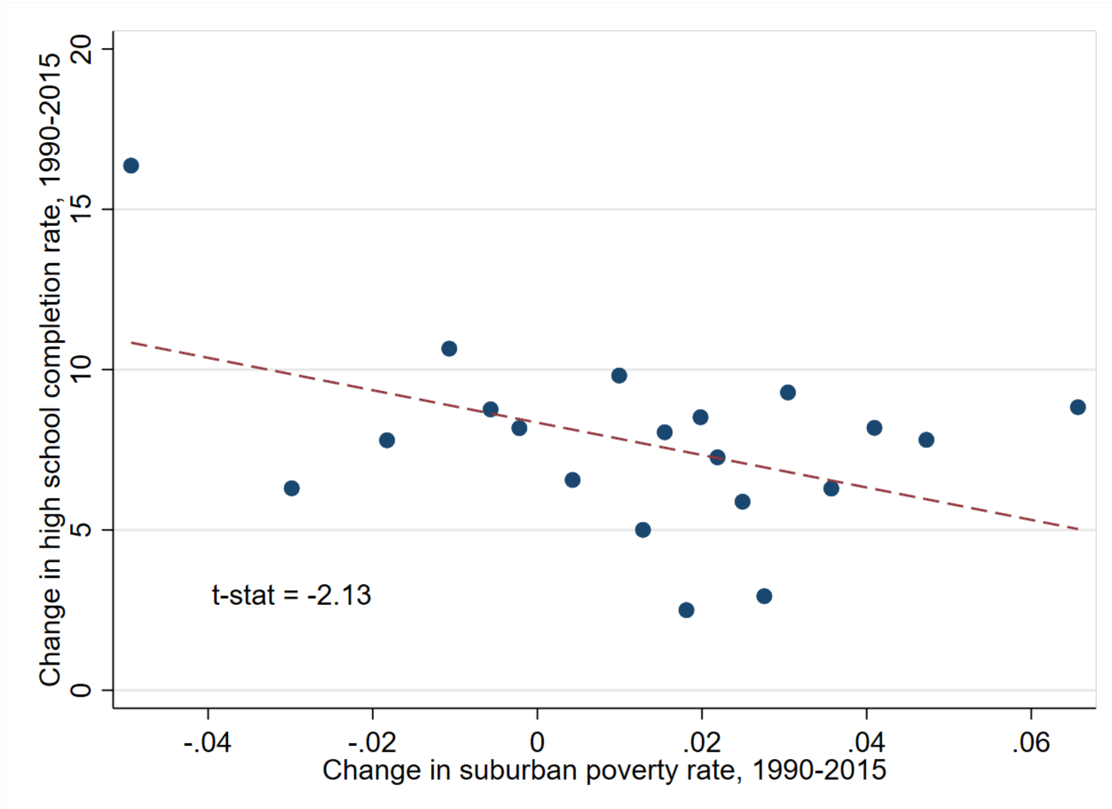
We aggregate suburban school districts together and compute the change in these measures of school completion over time for the suburban area of each MSA. Regressing the change in school quality against the change in suburban poverty rates[18] at the MSA level in Figure 13, we find that there is a statistically significant (t-stat = -2.13) negative relationship between these variables.

Due to the presence of peer effects in education, a decline in school quality may effect residents throughout the school district. As Patacchini et al. (2017) write, "if there are social norms that do not favor education among a group of close friends, then it may be difficult for these students to perform well at school." Though we do not claim that the relationship between suburban poverty and school quality is causal, a decline in the amenity value of suburban areas due to an increase in poverty would decrease welfare.

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

[18] 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.

Figure 13: School quality and suburban poverty



Note: We regress 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.

7.3 Policy Responses

The effects of suburban poverty on aggregate welfare discussed above are primarily due to changes in the the quality of, and funding for, local public goods. Addressing limited capacity in suburban anti-poverty programs, property tax shortfalls, and changing conditions in suburban schools could be a starting place for regional governments to address the effects of the changing spatial distribution of poverty.

Though governments may not be able to stop individuals from segregating themselves on the basis of race and income, there are tangible policies local governments can take to ameliorate the effects of suburban poverty. For example, local governments could reduce the impact that poverty has on communities by loosening the connection between local property values and school quality. That is, a system with more centralized financing of local public goods may lessen the effect that poverty has on suburban amenities and welfare. If school quality is less dependent on local poverty rates, residents may also be less likely to segregate themselves based on income.

8 Conclusion

In this paper, we explore the relationship between Black suburbanization and suburban poverty. Our model of residential choice demonstrates that Black suburbanization can increase suburban poverty because poorer non-black individuals may follow Black residents into the suburbs. We investigate empirically whether Black suburbanization caused suburban poverty to increase using a shift-share instrument based on the Great Migration. We find that the increase in the Black share of the suburban population caused suburban poverty, both overall and among the non-black population, to increase. We show that in suburbs that Black individuals entered, higher-income residents departed, bottom-quartile home prices declined, and lower-income individuals moved in.

While millions of Black families moved to the suburbs to improve their living conditions and the quality of their neighborhoods, destination responses and an ongoing longer-run processes of neighborhood demographic change may limit the increase in neighborhood quality they experience. The suburbs are changing, due to increasing poverty, in ways that reduce how much Black families' conditions and neighborhood quality can improve. As in Derenoncourt (2022), we have uncovered the limitations of large-scale movements to opportunity.

Delving into the consequences of the increase in suburban poverty, we show that the movement of poor individuals into suburban municipalities is associated with a decrease in overall property tax collections. We argue that the suburban poor are less able to access high-quality poverty-reduction services than the urban poor. Further, our results indicate that Black families are disproportionately exposed to the increase in suburban poverty.

Due to the relative dearth of anti-poverty programs in American suburbs (Allard 2017), we believe that addressing suburban poverty should be a policy priority. Tackling suburban poverty will not only be beneficial for the suburban poor, but also for their communities, including the many Black suburban residents now living amongst poverty. Although it is difficult for policymakers to address residential sorting and segregation, there are existing poverty-reduction programs that can be implemented in the suburbs. However, since most research about these programs focuses on urban areas, we do not yet know how effective these approaches would be in the suburbs. Given the expansion of poverty into American suburbs, and its myriad consequences, we believe this is a vital area for future research.

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9 Appendix

9.1 Appendix Tables

Table 9.1: Suburban poor population (millions)

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

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

Table 9.2: Demographic Changes in the Suburbs, 1990 to 2015-2019

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

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

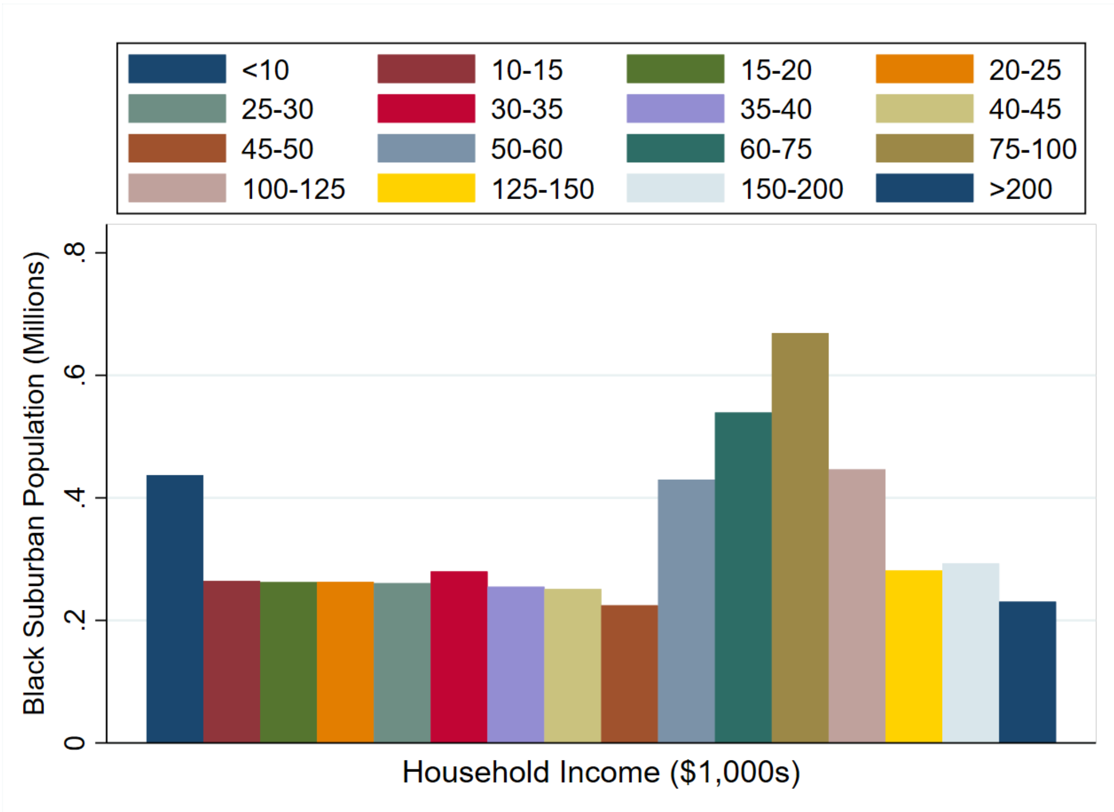
Table 9.3: Suburban Poverty Creation and Attraction

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

Numbers in millions. Data from Census and ACS microdata. The amount of suburban poverty creation and net poor in-migration to suburbs is imputed for 1990, 2000 and 2005 using the methodology described in the text.

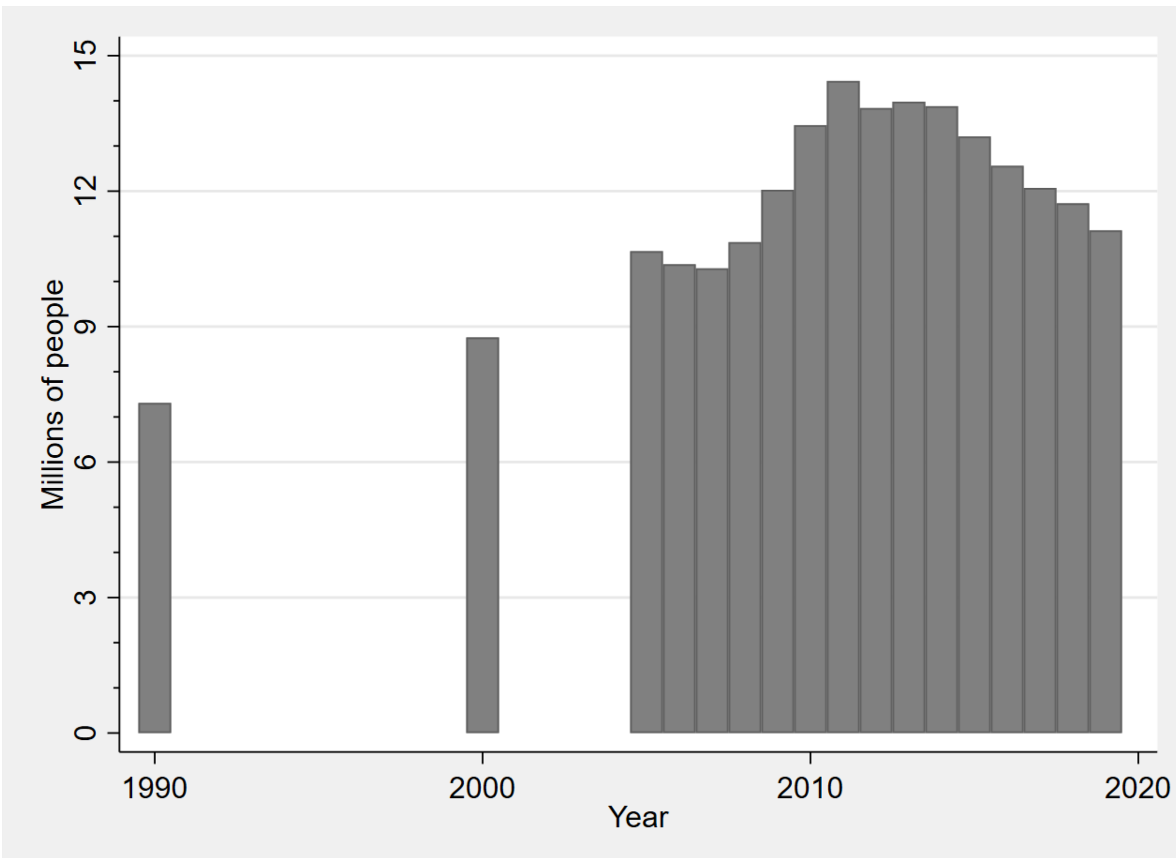
9.2 Appendix Figures

Figure 9.1: Annual income among suburban Black households, 2015-2019 ACS



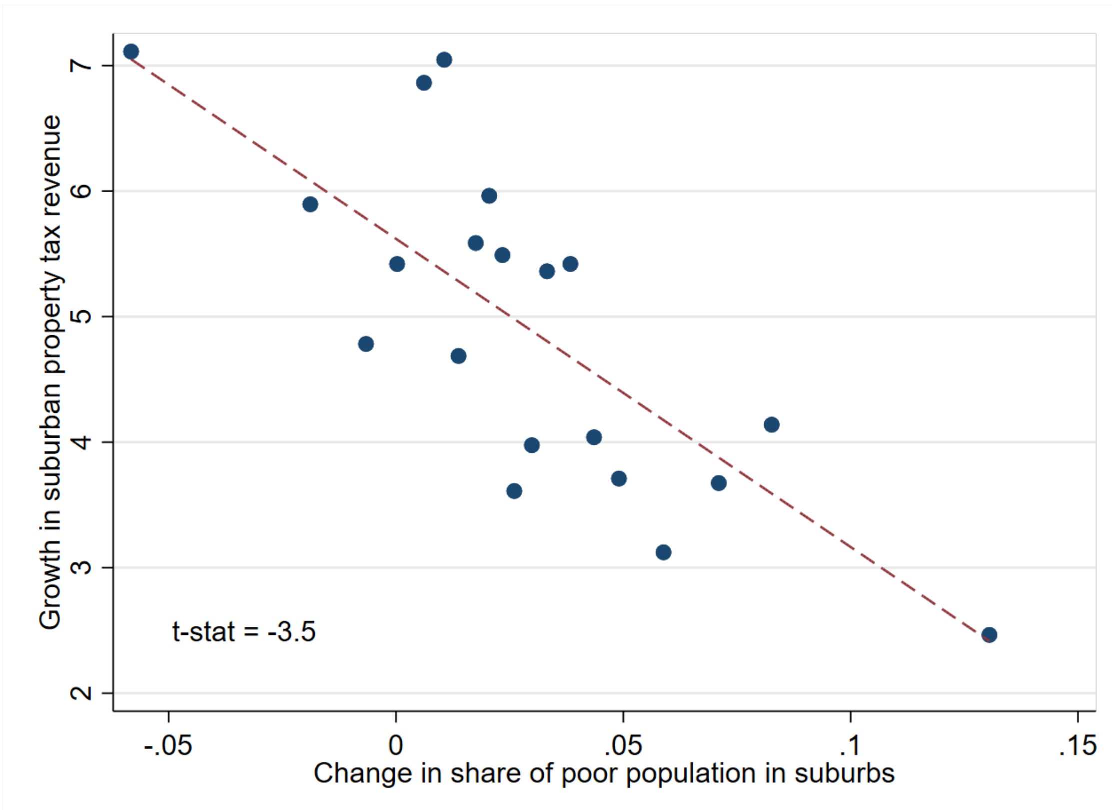
Note: Household income data for Black families aggregated using all suburban census tracts in the 2015-2019 five-year ACS.

Figure 9.2: Suburban Poor Population



Data from Census and ACS microdata.

Figure 9.3: Suburban property tax revenue and suburban poverty



This binscatter displays the relationship at the MSA level 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.

9.3 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 3:

$$s_k = \sum_i e_i \, s_{ik}, \; \tilde{\varepsilon}_k = \frac{\sum_i e_i s_{ik} \varepsilon_i}{\sum_i e_i s_{ik}} \tag{15}$$

The Stata program *ssaggregate* residualizes $\Delta_{1990,2015}\, x_i$ and $\Delta_{1990,2015}\, y_i$ from MSA-level equation 3 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 by taking an exposure-weighted average:

$$\bar{y}_k^{\perp} = \frac{\sum_i e_i s_{ik} y_i^{\perp}}{\sum_i e_i s_{ik}}, \bar{x}_k^{\perp} = \frac{\sum_i e_i s_{ik} x_i^{\perp}}{\sum_i e_i s_{ik}}, \tag{16}$$

9.4 Ray Construction

9.4.1 Overview

We observed that black residents moved out of the city and towards the suburbs in a particular direction. While the first black suburbanites tended to live close to existing urban African-American neighborhoods (Wiese 2019), we discovered that black individuals tended to move from those neighborhoods towards suburbs that are farther from the city center, likely in search of more affordable accommodations[19].

We draw a ray from the Central Business District (CBD) of each MSA to the center of the historic African-American neighborhood(s)[20], and extend this ray out towards the suburbs. This ray represents the direction in which we predict the black population primarily suburbanized, and we measure the distance between the city and suburbs d_i along these rays.

We use Chicago as an example of how we create 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 African-American neighborhood, and extend it outwards. Examining the spatial distribution of black residents of the Chicago area in 1960 and 2015 in Figure 9.4, the black population generally suburbanized in the directions that we predicted.

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

[20] We allow cities to have up to two African-American neighborhoods, depending on the geographic dispersion of their black population in 1960. For each African-American neighborhood, we find the population-weighted centroid of the group of neighboring tracts that have large black populations in 1960.

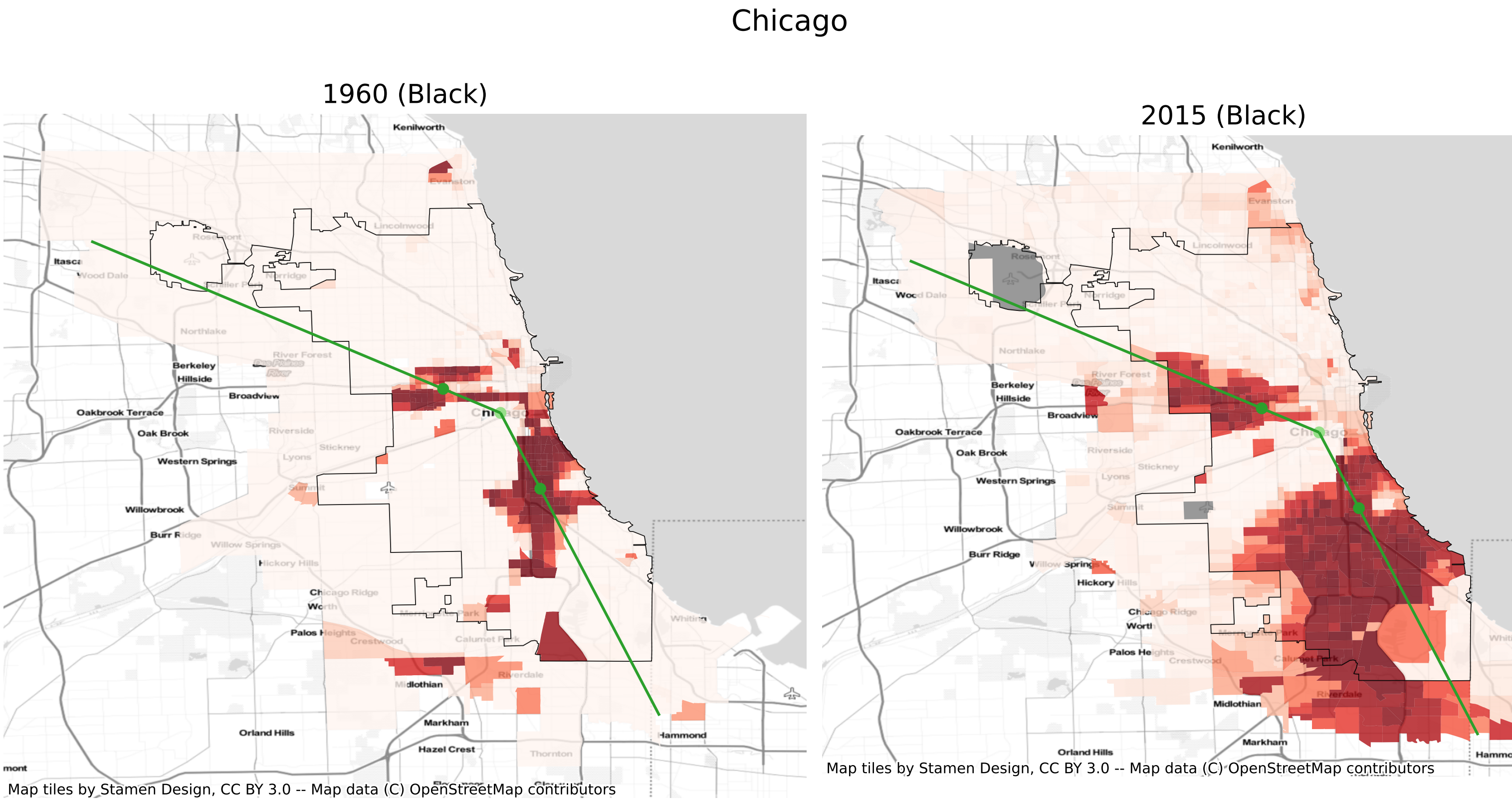


Figure 9.4: Direction of Suburbanization

9.4.2 Technical details

The directional ray for each MSA is constructed using the first (or second) principal city that has an identifiable place point in 1960[21][22]. We use these place points as a proxy for the city's central business district (CBD), which we generally consider the city center. Once we have our restricted sample of viable MSAs, we loop through each city-MSA pair to construct African-American 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 African-American neighborhood in that city. Otherwise, we construct two to capture the possibility of two distinct, separated neighborhoods in different quadrants. In both cases, we utilize an iterative process to choose the sample of tracts that will be used in constructing either one

[21] Place points are obtained using IPUMS NHGIS and they depict the locations of incorporated, unincorporated, and census-designated places identified in the census.

[22] In instances where the first prinicpal city does not have an identifiable place point, we try to use the second principal city listed in the MSA's title.

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 African American 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 each tract's centroid with the tract's 1960 black population. We can then recover the population-weighted centroid like any other weighted average:

$$Centroid_m = \frac{\sum_{t=1}^{T} p_{tm} Lat_{tm}}{\sum_{t=1}^{T} p_{tm}} \tag{17}$$

Where t is a tract in MSA m.

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 ids for each tract in the sample. Within these defined clusters, we then proceed to construct our own black-population-weighted-centroids as above in Equation 17.

With both the CBD and African-American neighborhood centers defined, we then create the rays extending outward toward the city limits, starting at the CBD, passing through the neighborhood center(s), and through the 2019 city boundary shapes.