Identifying Long-Run Neighborhood Effects via Race-Based Neighborhood Sorting

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Abstract: Children's adult outcomes are influenced by both their parents' socioeconomic status (SES) and the SES of the neighborhood where they grew up. We explicitly distinguish between these factors to identify long-run neighborhood effects. We estimate an ordered probit model of neighborhood choice and use it to infer how population shares of parental SES in each neighborhood vary along both observed and unobserved dimensions. We then regress the average observed outcomes in neighborhoods on these population shares to identify potential outcomes. Using race-based neighborhood sorting as an instrument, we estimate that about half of recent racial inequality in intergenerational mobility is explained by residential segregation.

Keywords: Neighborhood Effect, Neighborhood Sorting, Race, Intergenerational Mobility
JEL Classification Codes: C21, J15, J24, E24

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1 Introduction

There is a strong association between one's childhood neighborhood and subsequent adult outcomes. The blue line in Figure 1 shows that there is a $40,000 difference in the adult household incomes of those who spent their childhoods in neighborhoods with the highest and lowest levels of socioeconomic status (SES) as measured in 1990.

How much of the association between neighborhoods and outcomes is caused by the neighborhoods? The dashed red line in Figure 1 gives pause to a causal interpretation of the solid blue line. When comparing neighborhoods with the highest and lowest SES in 1990, there was a $100,000 difference in parents' household incomes. Thus, the difference in adult outcomes across children's neighborhoods in 1990 could be caused by their neighborhood environment, but could also be caused by household characteristics.[1]

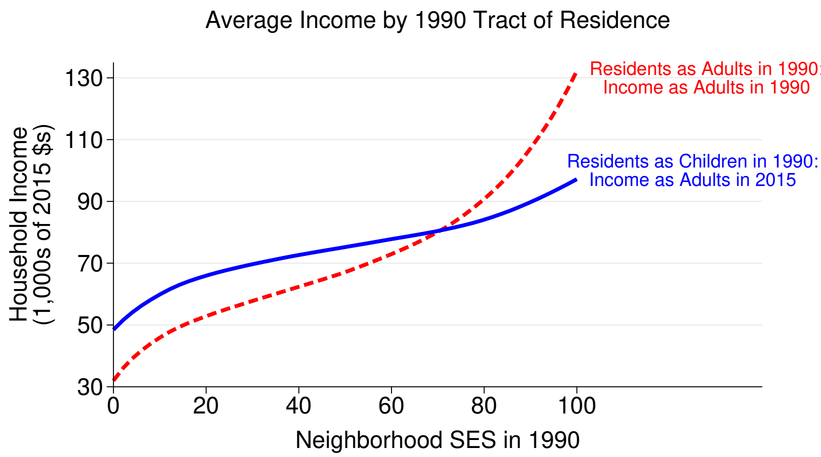


Figure 1: Future and Current Adult Household Income of Census Tract Residents in 1990
Note: The dashed red line shows a local linear regression of the adult household income of adults who were tract residents in 1990 as a function of their tract's neighborhood socioeconomic status (SES). Adult income in 1990 is from the 1990 United States Census, measured in 1,000s of 2015 $s for Black or white householders aged $\geq$ 15 in 1990. Adult neighborhood SES is measured for same population in 1990 via the 1990 US Census. The solid blue line shows a local linear regression of the adult household income of children who were tract residents in 1990 as a function of their tract's neighborhood SES. Adult income in 2014-2015, denoted "2015" in the figure, is from the Opportunity Atlas (OA), measured in 1,000s of 2015 $s for individuals aged 31-37 in 2014-2015. Childhood neighborhood SES is measured at ages 6-11 in 1990 using the 1990 US Census.

This paper uses a model to distinguish the effects of household SES from the effects of neighborhood SES on children's long-run outcomes. Our approach allows us to characterize neighborhood sorting in terms of both observed and unobserved household characteristics. We first estimate an ordered probit model of neighborhood sorting using tract-level Census data on household characteristics. We then use the estimated model to infer the joint distribution of observable and unobservable household characteristics in each Census tract. For each discrete neighborhood SES treatment level we identify potential outcomes using a tract level regression of average outcome estimates from the Opportunity Atlas (OA) on the tract-level population shares of discrete levels of observable and unobservable household SES.

[1] Appendix A shows that similar patterns hold for additional household characteristics thought to have causal effects on intergenerational mobility.

The first source of variation in our identification strategy is the general variation in the distribution of neighborhood SES across cities. The second source of variation in our identification strategy is the variation in the distribution of Black neighborhoods' SES across cities.

We refer to this second source of identifying variation as race-based neighborhood sorting. Black neighbors are a valuable amenity for Black Americans with a desire to avoid white hostility (Krysan and Farley (2002)). But across cities there is considerable variation in the SES of neighborhoods with a significant presence of Black residents (Aliprantis et al. (2024)), creating a tradeoff between access to economic opportunity and psychological safety. While researchers have for some time seen Black neighbors as an amenity for which households would exchange some amount of their neighbors' SES (Bayer et al. (2014)), recent evidence at the level of Census tracts (Aliprantis et al. (2024), Davis et al. (2024)) and blocks (Bayer et al. (2024)) has found that Black Americans trade off a surprisingly large quantity of their neighbors' SES in exchange for residing with Black neighbors. Similar results have also been found for schools (Caetano and Maheshri (2023)).

We estimate our ordered probit model using the method of simulated moments. The joint distribution of household characteristics is not available at the tract level, making maximum likelihood estimation of the model infeasible. Instead, we target moments of the marginal distributions of neighborhood SES conditional on specific household characteristics. We assume that observable characteristics lead to an increase in neighborhood SES through parameters that are constant across cities, but that the cutpoints in the ordered probit model are specific to each city. Moreover, we assume that Black households randomly sort into neighborhoods where at least 15 percent of residents are Black and then face cutpoints for such tracts that are again city-specific.

We use the estimated ordered probit model to infer the distribution of observables and unobservables in each tract. The strategy from Aliprantis and Richter (2020) of imputing each household's unobservables is infeasible without microdata containing the census tract of residence, which is not publicly available. Instead, we use the joint distribution of observables in each Public Use Microdata Area (PUMA), which is publicly available, and then use the model's estimated parameters to allocate those households into the tracts within each PUMA. This process yields an estimate of the joint distribution in each tract of the observables and unobservables from the sorting model. To obtain estimates of potential outcomes, or causal effects, conditional on discrete levels of these observable and unobservable levels of household SES, we simply regress observed outcomes from the OA on the population shares estimated from our model.

One set of results is provisional and likely to change with access to household-level data allowing for directly estimating households' unobservables at the tract level rather than imputing this distribution using PUMA-level data. Nevertheless, these preliminary results are suggestive that an important share of outcomes are caused by neighborhoods.

A second set of results is less likely to change with access to improved data. This set of results looks at how the supply of high SES Black neighborhoods in a city, as measured through the estimated model, affects the outcomes of Black residents in that city. These results suggest that residential segregation can account for about half of the difference between the intergenerational mobility of Black and white Americans.

Previous work has often adjusted for the endogeneity of residential sorting using railroad tracks as an instrument. For example, Ananat (2011) finds that increased segregation causes higher inequality in the outcomes of a city's Black and white residents. Chyn et al. (2022) find that the majority of racial inequality in intergenerational mobility could be explained by residential segregation.

2 Model of Neighborhood Effects

We use a a joint model of neighborhood sorting and potential outcomes that is a version of the neighborhood effects model from Aliprantis and Richter (2020) adapted from Heckman et al. (2006). Let the treatment D be discrete levels of neighborhood socioeconomic status (SES) and the instrument B be the share of Black residents in a neighborhood. We use deciles of the national distribution of US residents to define levels of D and define B as

$$D_i = \begin{cases} 1 \text{ if neighborhood SES } \in [0,10) \\ 2 \text{ if neighborhood SES } \in [10,20) \\ \quad \vdots \qquad\qquad \vdots \\ 10 \text{ if neighborhood SES } \in [90,100] \end{cases} \qquad B_i = \begin{cases} 0 \text{ if neighborhood percent Black } \in [0,15) \\ 1 \text{ if neighborhood percent Black } \in [15,100]. \end{cases}$$

Sorting into neighborhood treatments is specified as an ordered choice model

$$D_i = j \iff C^m_{j-1} + \gamma^m_{j-1} B_i \ < \ \mu(X_i) - V_i \ \leq \ C^m_j + \gamma^m_j B_i \tag{1}$$

where we assume an ordered probit specification with $V \sim \mathcal{N}(0,1)$. Potential outcomes are

$$Y_i(D) = \mu_D(X_i) + U_{Di}. \tag{2}$$

We impose that both the C^m_j and γ^m_j are increasing in j for all metros m. Sometimes we will refer to observables of the ordered choice model using their index $\mu(X)$; observables and unobservables of the potential outcomes will be referred to using level-specific labels as, for example, $\mu_1(X)$ and U_1.

This modeling approach assumes Black households randomly sort across neighborhoods' Black share first and then sort by neighborhood SES within that level of Black share. We plan to directly model selection into neighborhoods with a significant Black presence in a future revision of the paper.

Indexing tracts by τ, in this model the observed outcomes in a tract are a weighted average of the potential outcomes in that tract:

$$
\begin{aligned}
\mathbb{E}[Y_\tau] &= \int \mathbb{E}\big[Y(D_\tau)\,|\,X,V\big]\,dF_\tau(X,V) \\
&= \int \mathbb{E}\big[\mu_D(X) + U_D\,|\,X,V\big]\,dF_\tau(X,V)
\end{aligned}
\tag{3}
$$

Equation 3 illustrates that if there is no selection on observables, so that $\mathbb{E}[U_D|X,V] = \mathbb{E}[U_D|X]$, then potential outcomes can be estimated by adjusting for observables. We will focus on estimating a discretized version of Equation 3,

$$
\mathbb{E}[Y_\tau] \;=\; \sum_{d=1}^{10}\sum_{m=1}^{M}\sum_{n=1}^{N} 1\{D_\tau = d\}\,\beta^d(m,n)\;\pi_\tau(m,n) + \varepsilon_\tau \tag{4}
$$

where m captures discrete levels of observable index $\mu(X)$ and n captures discrete levels of the unobservable V. We will identify potential outcomes $\mathbb{E}\big[Y(d)\,|\,m,n\big]$ as the coefficients $\beta^d(m,n)$ in the regression in Equation 4.

3 Data

We use a combination of data sets that report variables at the levels of individuals, tracts, Public Use Microdata Areas (PUMAs), and Metropolitan Statistical Areas/Core Based Statistical Areas (MSAs/CBSAs), the last of which we will sometimes refer to as *metros*.

Because we define neighborhoods as Census tracts, estimation of the neighborhood sorting model is based primarily on tract-level data. While there exists publicly-available individual-level data from the US Census's American Community Survey (ACS) provided by IPUMS USA (Ruggles et al. (2024)) that includes demographic information and also reports an individual's PUMA of residence, Appendix C.3 describes that between 50 and 75 percent of the tract-level variation in our measure of neighborhood SES is within PUMA. For this reason, despite its coarser measurement of demographics, we estimate the model with tract-level data from the US Census provided by the National Historical Geographic Information System (NHGIS, Manson et al. (2023)).

Estimation of potential outcomes is based primarily on tract-level estimates of outcomes provided by the Opportunity Atlas (OA, Chetty et al. (2020)). The main outcome we study is total family income, and we obtain this outcome in terms of 2014 and 2015 dollars at the tract level by combining the OA data set with the ACS. We first calculate the distribution of family total income in 2014 and 2015 via the 2015 and 2016 samples of the IPUMS-USA ACS. We then use this distribution to convert the percentiles reported at the tract level by the OA to dollars. In both data sets we round percentiles to two decimal places (ie, the 12.34th percentile), and in the ACS we then assign the average income of those rounded to a given percentile.[2] We chose two decimals as a reasonable resolution for this variable because the resulting mean and median changes between

[2] Our distribution is for all families, while the OA distribution is for families with children.

discrete levels are, respectively, \$157 and \$0. While individual income inequality is driven by males (Chetty et al. (2020)), we focused on outcomes for males and females because inequality is similar across men and women when measured at the household level (Binder et al. (2022)). Appendix C.1 provides further details.

At times we compare the OA estimates with those from the National Longitudinal Survey of Youth (NLSY97). Two details of note for these comparisons are that (i) the birth cohorts of the OA and NLSY97 are, respectively, 1978-83 and 1980-1984; and (ii) The OA sample comprises children born in the US or who came to the US as authorized immigrants, and the NLSY97 sample comprises respondents representative of people living in the United States during the initial survey round (1997).

We rank tracts in terms of the socioeconomic status (SES) of their residents to create the neighborhood SES index used in Aliprantis (2017) and Aliprantis and Richter (2020). We first rank tracts in 1990 in terms of their poverty rate, the share of adults 25+ with a high school diploma, the share of adults 25+ with a BA, the Employment to Population Ration for adults 16+, the labor force participation rate for adults 16+, and the share of families with children under 18 with only a mother or father present.[3] Neighborhood SES is the ranking of a tract in terms of the first principal component these six tract-level rankings.

Broadly speaking:

<u>To estimate the neighborhood sorting model</u>, we use

- Tract-level counts of residents by demographic characteristics
  - Provided by the National Historical Geographic Information System (NHGIS)
    - 1990 Census short- and long-form variables
- MSA/CBSA-level counts of residents by demographic characteristics
  - Provided by the National Historical Geographic Information System (NHGIS)
    - 1990 Census short- and long-form variables

<u>To estimate potential outcomes</u>, we use

- Tract-level estimates of average outcomes by demographic characteristics
  - Provided by the Opportunity Atlas (OA).
    - Household income is based on information in W-2 income tax returns in adulthood for respondents aged 6-11 in the 1990 Census
    - Educational attainment is measured in the Census 2000 long form or the 2005-2015 waves of the American Community Survey (ACS)
    - Incarceration is based on the 2010 US Census short form
  - For household income, percentile estimates for 2014 and 2015 provided by the OA are combined with the income distribution measured in the 2015 and 2016 waves of the American Community Survey provided by IPUMS USA

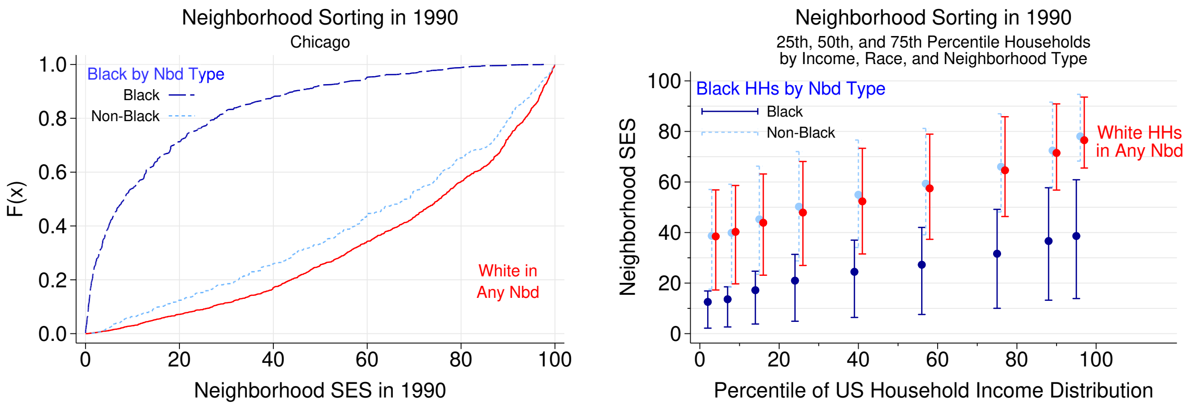
[3]Because the outcome estimates in the OA are provided in 2010 Census tract boundaries, we impute count estimates from 1990 boundaries into 2010 boundaries using the Longitudinal Tract Data Base (LTDB) described in Logan et al. (2014), Logan et al. (2016), and Logan et al. (2021). We note that this is a non-trivial detail.

- CBSA-level counts of residents by demographic characteristics
  - 1990 Census short- and long-form variables provided by the National Historical Geographic Information System (NHGIS)

3.1 Race-Based Neighborhood Sorting

Figure 5b gives a sense of the variation in neighborhood SES generated by race-based neighborhood sorting. The figure shows the Cumulative Distribution Functions (CDFs) of neighborhood SES for various groups in Chicago in 1990. Two features stand out. First, the dashed light blue line showing the CDF of Black households in non-Black neighborhoods is remarkably similar to the red line showing the CDF for white households (in any neighborhood). In other words, when Black households reside in non-Black neighborhoods (where less than 15 percent of residents are Black), they sort across neighborhood SES similarly to white households. Second, the dark blue dashed line shows the CDF of Black households in Black neighborhoods. The gap between the dark and light blue lines shows that Black households trade off extremely large amounts of neighborhood SES when residing in Black neighborhoods.

Figure 2b reproduces the result from Aliprantis et al. (2024) that the gap in neighborhood SES between Black households in Black and non-Black neighborhoods is not primarily driven by income differences between these two groups. At all levels of income, Black households sort similarly to white households. This is shown by comparing the light blue lines and the red lines, which show, respectively, the 25th to 75th percentiles of each group's distribution of neighborhood SES, with dots displaying each group's median. Instead, what we see is that at all levels of income, Black households trade off large amounts of neighborhood SES when residing in Black neighborhoods. This fact is shown by comparing the solid dark blue and dashed light blue distributions that display the gap in neighborhood SES for Black households when residing a Black or non-Black neighborhood. As an example, in 1990, in the top decile of the household income distribution, the median Black household in a Black neighborhood was in a tract 40 percentile points lower-ranked than the median Black household in a non-Black neighborhood.

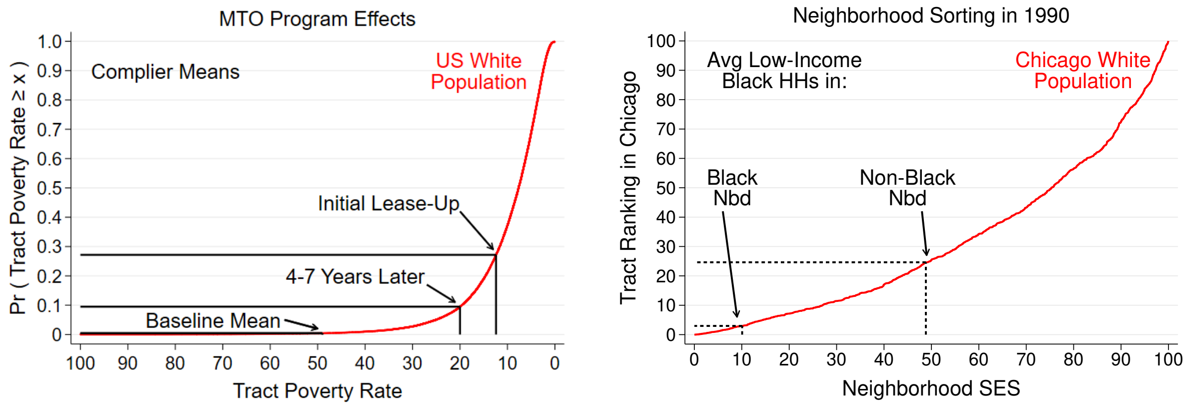


(a) Chicago

(b) The US

Figure 2: Race-Based Neighborhood Sorting in 1990
Note: The left panel displays the Cumulative Distribution Functions (CDFs) of households over neighborhood socioeconomic status (SES) in Chicago in 1990. The red line shows the CDF of white households, the dashed light blue line shows the CDF of Black households in non-Black neighborhoods, and the dashed dark blue line shows the CDF of Black households in Black neighborhoods. The right panel reports the 25th, 50th, and 75th percentiles of these groups' distributions over neighborhood SES after also conditioning on household income bins. These moments of the groups' distributions are reported at the midpoint of each bin for which income is reported publicly at the tract level in Census data.

Race-based neighborhood sorting generates massive variation in neighborhood SES. To illustrate this point, Figure 3 compares the neighborhood sorting of compliers in the Moving to Opportunity (MTO) experiment with the neighborhood sorting of Black households in Chicago in the first quintile of the US income distribution. Figure 3a shows that the baseline mean across the five MTO sites was the first percentile of neighborhood non-poverty rates for the population of non-Hispanic white Americans in 2000. Initial lease-ups were near the 30th percentile of this distribution and medium-term locations were ranked on average near the 10th percentile neighborhood. Figure 3b shows that in Chicago in 1990, the average of Black households with first-quintile incomes was near the 10th percentile of neighborhood SES. However, for Black households in Chicago in this same low-income group, those residing in non-Black neighborhoods were on average near the median of neighborhood SES. In other words, race-based neighborhood sorting in Chicago in 1990 generated differences in neighborhood SES for low-income Black households that was greater than the differences experienced in MTO compliers in their *initial* lease-up locations. Appendix Figure 5 presents similar data to show that race-based neighborhood sorting of Black households in Chicago who had income in the top quintile of the US distribution experienced similar magnitudes of differences in neighborhood SES as suburban movers in the Gautreaux housing mobility program.



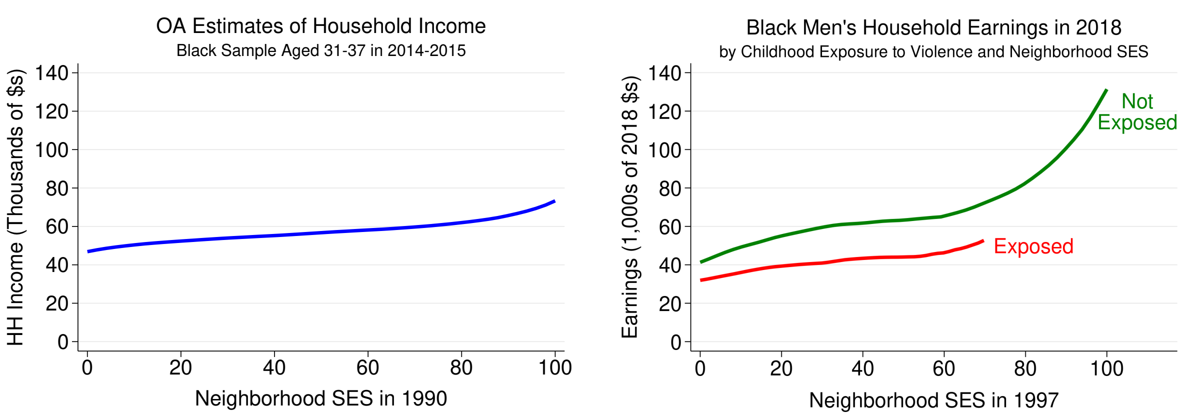
(a) Moving to Opportunity

(b) Chicago

Figure 3: Comparing Moving to Opportunity with Race-Based Neighborhood Sorting in Chicago
Note: Panel a shows mean tract poverty rates in the 2000 Census from Orr et al. (2003), with baseline poverty rates taken from Exhibit 2.7, complier mean in initial lease-up location taken from Exhibit 2.3, and complier mean 4-7 years after randomization taken from Exhibit 2.5. Panel b shows the mean neighborhood SES for Black households in the bottom quintile of the overall US household income distribution in 1990. Black neighborhoods are defined as Census tracts where at least 15 percent of residents are Black.

3.2 Measurement in High SES Neighborhoods

Figures 4a and 4b show that the OA and NLSY97 paint a different descriptive picture about the outcomes of Black males who grew up in high SES neighborhoods. In Figure 4a we see that in the OA adult household income increases only slightly as childhood neighborhood SES increases. In contrast, Figure 4b, reproduced from Aliprantis and Tauber (2024), shows that the increase in Black men's adult household earnings is very steep as neighborhood SES increases in the top half of neighborhoods.



(a) Opportunity Atlas (OA)

(b) NLSY97

Figure 4: Black Males' Household Income in Adulthood and Neighborhood SES in Childhood

We plan to investigate two possible explanations for the differences in panels (a) and (b) of

Figure 4. First, it is possible that functional form estimation assumptions in Chetty et al. (2020) could bias conditional expectation function estimates. The functional form assumption in Chetty et al. (2020) is that up to an affine transformation, the shape of the intergenerational mean outcome conditional on parental income and race is similar in a given neighborhood as it is for the nation. Figure 5 shows the sample selection of tracts noted in Aliprantis et al. (2024) which is part of the reason why such functional form assumptions are both necessary and might be problematic; most high SES tracts did not have a large enough sample of Black males to reliably estimate their mean outcomes. However, it is also possible that the self-similarity estimation assumptions in Chetty et al. (2020) do not bias OA estimates. A second possibility is that estimates from the NLSY97 sample reflect noise or outlier-driven bias due to a small sample size.

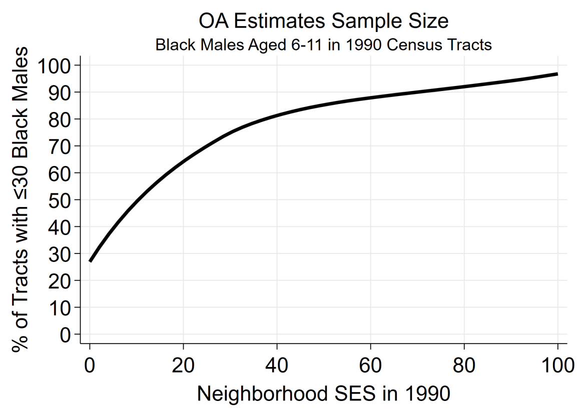


Figure 5: Black Male Sample Size in the Opportunity Atlas (OA) by Neighborhood SES

3.3 Estimation Sample

We estimate the model using the 19 largest CBSAs in 1990 as ranked by the number of Black residents. In order from largest to smallest Black populations, these are New York, Chicago, DC, Los Angeles, Philadelphia, Detroit, Atlanta, Miami, Houston, Baltimore, Dallas, New Orleans, Memphis, St. Louis, San Francisco, Virginia Beach, Cleveland, Charlotte, and Richmond. This sample is chosen because smaller metros do not all have Black neighborhoods in each decile of neighborhood SES. Appendix C.4 provides more details on the metro-level distribution of Black population size.

4 Estimation Technique

We will often refer to two definitions of discrete heterogeneity in the model:

Observable Types

- The 54 possible discrete combinations of household i's observable characteristics X_i;
- 9 levels of income $\times$ 3 levels of ed. attainment $\times$ 2 levels of household marital status.

Household Types

- The $M \times N$ discrete combinations of observable and unobservable characteristics possible when dividing both the observable index $\mu(X_i)$ and unobservables V_i into discrete levels.
- We will denote $\mu(x) = m \in \{1, 2, \ldots, M\}$ and $u_D = n \in \{1, 2, \ldots, N\}$

Our goal will be to estimate the joint distribution of observables and unobservables, in discrete levels, in each Census tract τ, $\pi_\tau(m, n)$. This will allow us to identify potential outcomes by estimating an Ordinary Least Squares (OLS) regression of tract-level OA outcome estimates on our model's implied population shares:

$$\overbrace{\mathbb{E}[Y_\tau \mid race]}^{\text{OA}} = \sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{d=1}^{10} \overbrace{1\{D_\tau = d\}}^{\text{1990 Census}} \mathbb{E}[Y(d) \mid race, m, n] \; \overbrace{\pi_{\tau,race}(m, n)}^{\text{our model}} + \epsilon_\tau \tag{5}$$

$$= \sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{d=1}^{10} 1\{D_\tau = d\} \beta^d(race, m, n) \; \pi_{\tau,race}(m, n) + \epsilon_\tau \tag{6}$$

There is a direct path to estimating $\pi_\tau(m, n)$ with household-level data including both observables X_i and neighborhood SES for the tract of residence τ. In that case, one would estimate the ordered probit model via Maximum Likelihood (ML) and then, following Aliprantis and Richter (2020), one would use those estimates to impute the V_i of each household i with X_i in tract τ.

Our identification strategy is a bit different because we do not have household-level data on the joint distribution of the X in each tract. Instead, we have tract-level data on the marginal distributions of the X in each tract, with the joint distribution of the X only available at the larger level of PUMAs. Thus, we estimate the ordered probit model via the Method of Simulated Moments (MSM). Then we use those estimates, together with what we know about PUMAs and the neighborhood SES of tracts within each PUMA, to estimate $\pi_\tau(m, n)$.

4.1 Step 1: Estimating the neighborhood sorting model

We assume the ordered probit model represents the neighborhood sorting of households with children aged 6-11 in 1990. In the NHGIS tract-level data we do not observe the full joint distribution of neighborhood SES and household characteristics X_i. Instead, we observe marginal distributions of neighborhood SES by groups of characteristics X_i.

We will sometimes refer to the cutpoints for deciles of quality as $C_1, C_2, \ldots, C_9$ or $C_{10}, C_{20}, \ldots, C_{90}$, and we will refer to percentiles of neighborhood SES as indexed by P_p. Given a parameter value $\widehat{\theta}$, the model specified in Section 2 implies conditional moments

$$\widehat{F}_{SES}(P_{10}|\text{inc}, \text{ed}, \text{mar}) = \Phi[\widehat{\mu}(\text{inc}, \text{ed}, \text{mar}) - \widehat{C}_{10}],$$

which can be marginalized as

$$\widehat{F}_{SES}(P_{10}|\text{inc}=1) = \sum_{\text{ed}}\sum_{\text{mar}} Pr(\text{ed},\text{mar}|inc=1)\Phi[\widehat{\mu}(\text{inc}=1,\text{ed},\text{mar}) - \widehat{C}_{10}]$$

where the joint distribution $Pr(\text{inc},\text{ed},\text{mar})$ is estimated from the IPUMS USA data at the metro level. Then the sum of squared errors for the marginal distribution of neighborhood SES by income levels would be

$$SSE(\text{inc}) = \sum_{p\in\{10,20,\ldots,90\}} \sum_{inc=1}^{9} [\widehat{F}_{SES}(P_p|\text{inc}=inc) - F_{SES}(P_p|\text{inc}=inc)]^2$$

and the overall loss function is simply a Sum of Squared Errors (SSE) for several marginal distributions

$$L(data,\widehat{\theta}) = SSE(\text{inc}) + SSE(\text{ed}) + SSE(\text{mar}).$$

It should be noted that while the model is specified at the household level given the presence of children aged 6-11, some of the observed characteristics are measured at the individual rather than the household level. These include the distribution of neighborhood SES by race × sex × age groups; as well as the distribution of neighborhood SES by race × educational attainment groups. Likewise, the distributions of neighborhood SES by race × income groups are measured over all households, regardless of whether they contain any children aged 6-11; and the distributions of neighborhood SES by race × marital status is for all households with children 0-18, not just those in our desired age range.

To summarize the homogeneity and heterogeneity assumed in the model, we assume that the

- $\mu(X)$ parameters are common across cities
- C_j parameters are metro-specific
- C_j^B parameters are metro-specific

4.2 Step 2: Estimating population shares in each tract

A key part of our identification strategy is linear interpolation between the cutpoints C_j of the estimated model following Aliprantis and Richter (2020). This allows us to estimate the continuous cost function $C(SES)$ at any continuous level of neighborhood SES for $SES \in (0,100)$. Household-level data on the joint distribution of observables X in each tract τ would facilitate the identification of $\pi_\tau(X,V)$. In that case, we could simply use the continuous cost function to infer each individual household's V_i, given their X_i and the level of SES in their tract of residence, and then simply estimate π in each tract using the sample analogue.

The fact that we do not observe the joint distribution of X in each tract complicates the identification of tract-level population shares $\pi_\tau(X,V)$. Identification of population shares follows from combining three pieces of information:

- We know the joint distribution of X in each PUMA from the 1990 Census.
- Given a household type $X = x$, the estimated ordered probit model implies the probability of being in each tract within a given PUMA (there are usually 25-30 tracts per PUMA).
- The estimated model implies a distribution of V conditional on being in tract τ with observables $X = x$.

By the definition of conditional probability, we have that

$$Pr(X = x, V|\tau = t) = \underbrace{Pr(V|X = x, \tau = t)}_{\text{Term 1}} \underbrace{Pr(X = x|\tau = t)}_{\text{Term 2}}. \tag{7}$$

Before focusing on the estimation of Terms 1 and 2, let us look at the tracts within a given PUMA p. After ordering the tracts in PUMA p as $k = \{1, 2, \ldots, K\}$, there is a modified version of Equation 2 that holds:

$$\tau_i = k \iff C^m(q_{k-1}) \;<\; \mu(X_i) - V_i \;\leq\; C^m(q_k). \tag{8}$$

This implies that the support of V (ie, $\mathbb{R}$) is partitioned for a given value of $X = x$ by the intervals

$$\tau_i = k \iff \mu(x_i) - C^m(q_k) \leq \quad V_i \;<\; \mu(x_i) - C^m(q_{k-1}) \tag{9}$$

This allows us to estimate **Term 2** as

$$Pr(X = x|\tau_k) = \frac{(\#X = x \in \tau_k)}{\sum_{z=1}^{54}(\#X = z \in \tau_k)}$$

where

$$(\#X = x \in \tau_k) = \underbrace{(\#X = x \in p)}_{\text{IPUMS USA}} * \underbrace{[\Phi(\mu(x) - C^m(q_{k-1})) - \Phi(\mu(x) - C^m(q_k)]}_{\text{estimated model}}.$$

Now turning to the estimation of **Term 1**, we have that

$$f(V|X_i = x, \tau_i = k) = \begin{cases} \frac{\phi(V)}{\Phi[\mu(x) - C^m(q_k)] - \Phi[\mu(x) - C^m(q_{k-1})]}, & \text{if } V \in [\mu(x) - C^m(q_k),\ \mu(x) - C^m(q_{k-1})] \\ 0, & \text{otherwise.} \end{cases}$$

Thus we can obtain the discrete case

$$\pi_\tau(m, n) = Pr(\overline{v} = n \,|\, \mu(X) = m, \tau) Pr(\mu(X) = m \,|\, \tau)$$

One note, as shown in Appendix Figure 9, is that just under 20 percent of adjacent tracts within a PUMA are within 0.1 percentile points of each other's neighborhood SES ranking. When this occurs, we treat the two tracts as one tract. Such pairs are recently split tracts about 85 percent of the time.

4.3 Step 3: Estimating potential outcomes

With ten levels of neighborhood SES, or $D \in \{1, 2, \ldots, 10\}$, we choose three levels of each for observables $m \in \{1, 2, 3\}$ and unobservables $n \in \{1, 2, 3\}$. This results in $10 \times 3 \times 3 = 90$ potential outcomes to estimate of the form

$$\mathbb{E}[Y(d)|\mu(x) = m, u_D = n].$$

In the OA outcome estimate, we observe many tract-level observations of outcomes given neighborhood treatment level, $\mathbb{E}[Y|D = d, \tau = t]$, where

$$\mathbb{E}[Y|D_\tau = d] \;=\; \sum_{m=1}^{3}\sum_{n=1}^{3} \mathbb{E}[Y(d)|m, n]\;\pi_\tau(m, n) \tag{10}$$

Thus, given our estimates of population shares in each tract $\widehat{\pi}_\tau(m, n)$, we can recover the potential outcomes of interest as the coefficients in the following regression:

$$Y_\tau \;=\; 1\{D_\tau = d\} \sum_{m=1}^{3}\sum_{n=1}^{3} \beta^d(m, n)\;\widehat{\pi}_\tau(m, n) + \epsilon_\tau. \tag{11}$$

We estimate Equation 11 via Ordinary Least Squares (OLS).

5 Estimation Results

5.1 Neighborhood Sorting Model

Figure 6 reports results of the ordered probit model. The red lines show the continuous cost functions in non-Black neighborhoods, $C^m(q)$, generated by linearly interpolating between the cutpoints $\{C^m_j\}_{j=1}^9$ for the metros $m =$ Chicago, Philadelphia, Atlanta, and DC. The blue lines show the analogous cost functions $C^{B,m}(q) = C^m(q) + \gamma^m(q)$ in Black neighborhoods. A few points stand out. First, the cost functions in Black neighborhoods tend to be much higher than in non-Black neighborhoods. This is consistent with the relatively low supply of high SES Black neighborhoods documented in Aliprantis et al. (2024). Second, we can see that there is variation across cities in the cost functions, especially for the cost functions in Black neighborhoods. Black households with the same observables will sort into much higher SES neighborhoods in Atlanta than in Chicago or Philadelphia. DC is an outlier, with a cost function in Black neighborhoods that approaches the cost functions in non-Black neighborhoods in other cities.

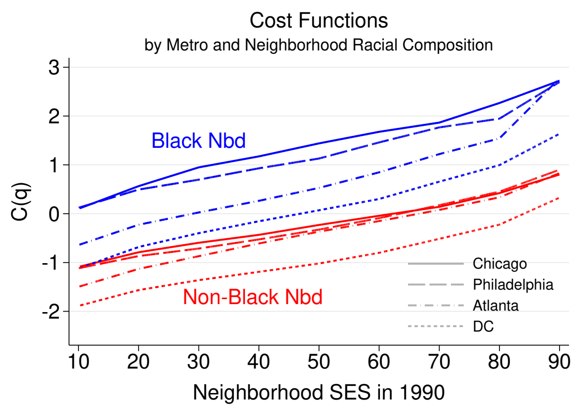


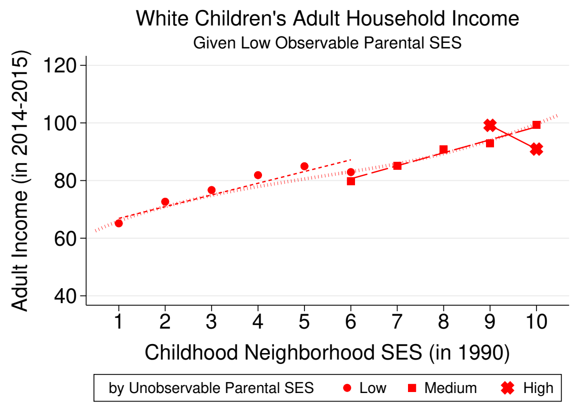
Figure 6: Continuous Cost Function Estimates Constructed via the Ordered Probit Model
Note: This figure shows estimates of the ordered probit model. The ordered probit model yields cutpoint estimates at the 10th, 20th, . . . , and 90th percentiles of neighborhood SES. These cutpoints, together with linear interpolations between them, are displayed in red for non-Black neighborhoods. The additional cost when residing in a Black neighborhood is analogously presented in the blue lines.

5.2 Potential Outcomes

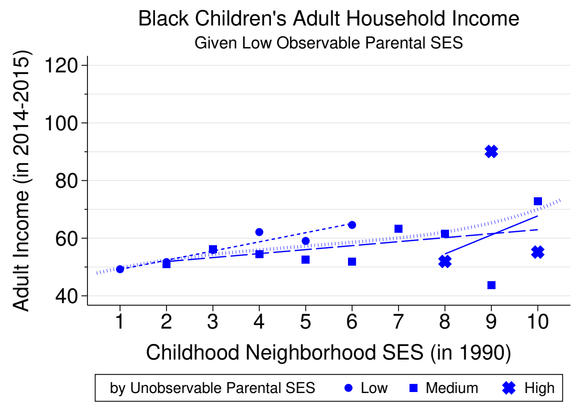
Figure 7 shows the estimates obtained from estimating Equation 11 via OLS, recalling that the regression coefficients represent the potential outcomes of interest. Among the results in this working paper, the results reported in these figures are the results most likely to change in future estimation with full access to Census data as opposed to these estimates based on publicly-available data. In these figures we see dots, squares, or X's as symbols showing the potential outcome estimate for a discrete level of neighborhood SES, observable parental SES, and unobservable parental SES (ie, $D \times \mu(X) \times V$). The dotted red and blue lines show the unconditional outcomes for, respectively, white and Black children.

These results indicate that the association between childhood neighborhood SES and adult income is largely causal. We consider there to be four primary threats to this interpretation. First, the model could be mis-specified due to the identification assumptions required to estimate the model with publicly-accessible data. Second, the model could be mis-specified in important ways because we have not modeled Black households' selection into Black neighborhoods. Third, there could be basic measurement issues as highlighted by the earlier comparison of the OA and NLSY97 descriptive statistics. And fourth, there could be considerable differences in observable or unobservable parental SES bins within the relatively large tercile aggregation bins we use for each.[4] We will revisit these results once we have access to the full Census data necessary to estimate the model under weaker identifying assumptions and to have some insight into the measurement discrepancy between the OA and the NLSY97.

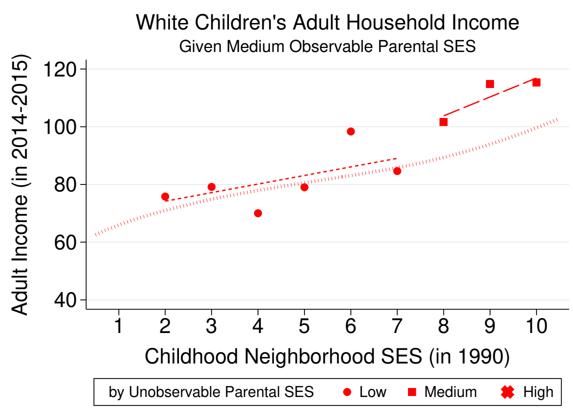
[4] For a related example, see Gelman and Auerbach (2016).



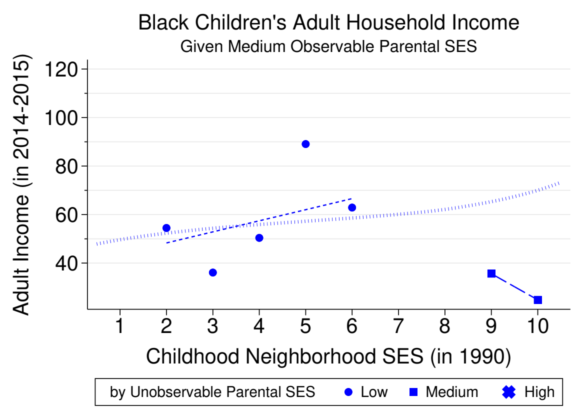
(a) Low $\mu(X)$ White Households



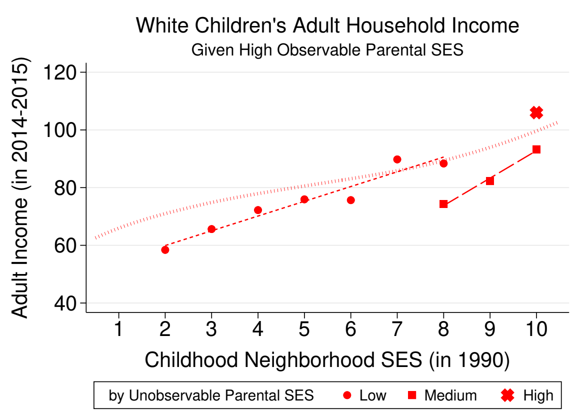
(b) Low $\mu(X)$ Black Households



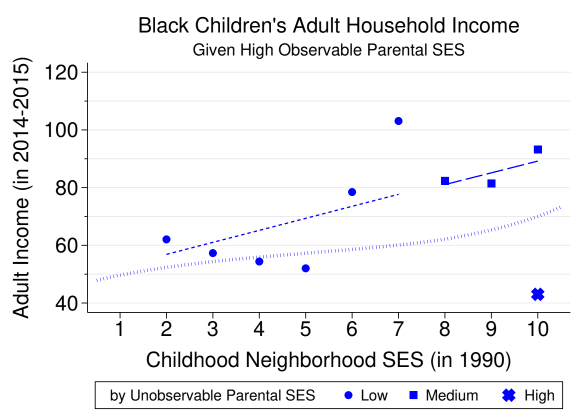
(c) Middle $\mu(X)$ White Households



(d) Middle $\mu(X)$ Black Households



(e) High $\mu(X)$ White Households



(f) High $\mu(X)$ Black Households

Figure 7: Estimates of Potential Outcome for Adult Household Income

Note: These figures show the regression coefficients of Equation 11 estimated via OLS where the independent variables are tract-level population shares of observable and unobservable parental SES (or $\mu(X)$ in the sorting model) and the dependent variables are the average race-specific family income observed in adulthood. The short dashed, long dashed, and solid lines show the best fit lines for these potential outcome estimates, respectively, for children with low, medium, and high unobservable parental SES. The dotted red and blue lines show the unconditional mean adult outcomes of, respectively, white and Black children.

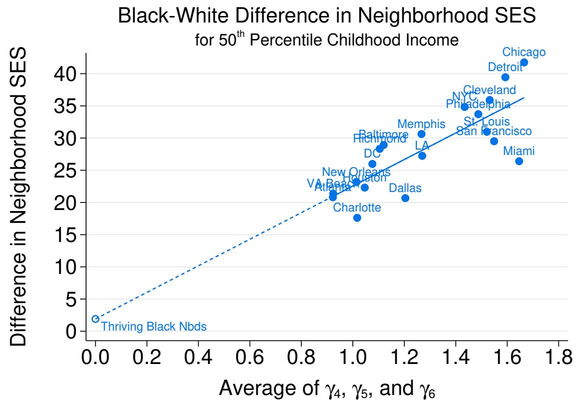
6 Thriving Black Neighborhoods

Our model is well suited to answer the question: What is the contribution of residential segregation to overall racial inequality? To answer this question one could consider a counterfactual where the γ parameters in the ordered choice model were all set to 0. The γ parameters in the ordered probit model represent the additional "cost" to Black households, who are otherwise similar to white households, in attaining a given level of neighborhood SES. One interpretation of such a counterfactual would be that it represents thriving Black neighborhoods. If the supply of neighborhood SES in Black neighborhoods were identical to the supply in non-Black neighborhoods, then Black households would not face a tradeoff between the share of their Black neighbors and their neighbors' SES. One could also interpret this counterfactual as one in which race is no longer salient for neighborhood sorting.

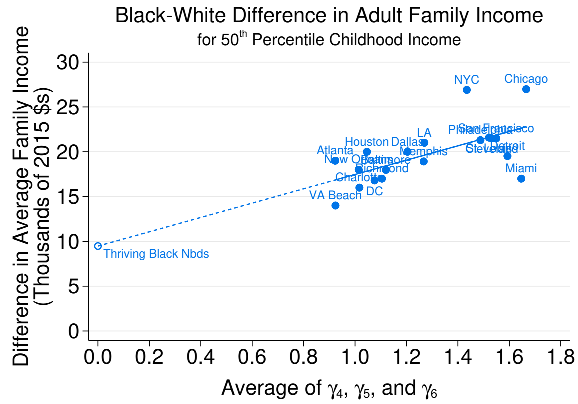
Figure 8a shows the difference between the neighborhood SES of a metro's Black and white populations as a function of the metro-specific γ parameters estimated in the ordered choice model. The y-axis shows the difference in neighborhood SES calculated at the median of the US household income distribution, and the x-axis shows the average of γ_4, γ_5, and γ_6, the parameters representing the extra cost of sorting into a Black neighborhood at the 40th, 50th, and 60th percentiles of the US neighborhood distribution. We can see that there is a clear relationship between the average γ is a metro and the gap between the neighborhood SES of its Black and white residents.

The point in the very bottom left of Figure 8a shows us the predicted racial difference in neighborhood SES if we were to extrapolate from the observed relationship to a value of $\gamma = 0$, or a scenario of *thriving Black neighborhoods*. This point illustrates that if γ were set to 0, the model predicts that there would be essentially no difference in the neighborhood SES of Black and white households at the 50th percentile of income. This extrapolation and the correlation in the observed data can be seen as evidence that the model broadly fits the data.

Figure 8b shows the difference between adult family income for a metro's Black and white populations as a function of the metro-specific γ parameters estimated in the ordered choice model. We again see a clear relationship where increased γ parameter in a metro predicts a greater difference between Black and white outcomes. Figure 8b allows for extrapolation to the point of $\gamma = 0$, or *thriving Black neighborhoods* in terms of this difference. The point at the very bottom left of Figure 8b shows that the estimated model predicts an approximately 50 percentage point reduction in the gap between the household incomes of Black and white family in the counterfactual of *thriving Black neighborhoods*. These estimates of the effects of segregation add to those in the literature using alternative identification strategies, such as those in Ananat (2011), Chyn et al. (2022), Cox et al. (2025), and Chetty et al. (2020).



(a) Differences in Treatment at 50th Percentile



(b) Differences in Outcomes at 50th Percentile

Figure 8: Differences in Childhood Treatment and Adult Outcomes by Metros' Estimated Cost γ of Accessing a Black Neighborhood

7 Conclusion

This paper contributes to the growing literature on the sources of geographic heterogeneity in intergenerational mobility (Cholli et al. (2024), Eshaghnia et al. (2023), van Ham et al. (2018)) and the effects of residential segregation (Ananat (2011); Chyn et al. (2022); Cox et al. (2025)). We specified a Rubin Causal Model in which parental SES and neighborhood SES jointly determine children's adult outcomes. We estimated the selection into neighborhood treatments using an ordered probit model that allowed us to estimate the population shares of parental SES in each Census tract along both observed and unobserved dimensions. Estimating a regression of tract-level outcome estimates from the Opportunity Atlas (OA) on these population shares allowed us to recover potential outcome estimates. These estimates imply that much of the variation in outcomes across neighborhoods is due to neighborhood effects. Moreover, when we used race-based neighborhood sorting as an instrument, we estimated that about half of recent racial inequality in intergenerational mobility is explained by residential segregation.

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Appendix to
"Identifying Long-Run Neighborhood Effects via Racialized Neighborhood Sorting"

Dionissi Aliprantis Daniel Hartley Chris Muris

A Neighborhood Sorting in 1990

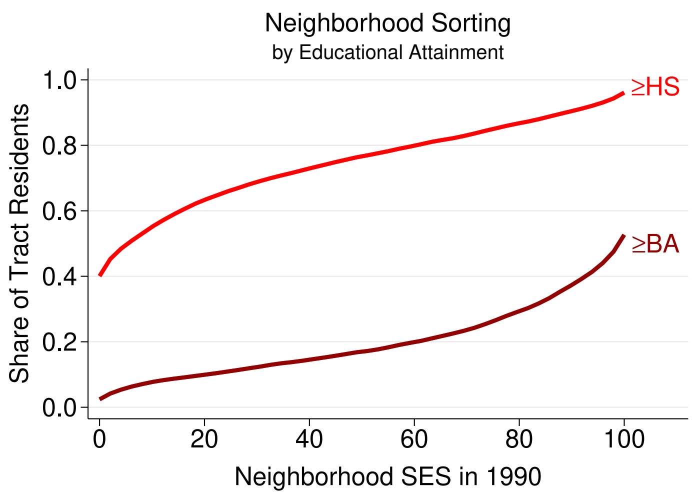


Figure 1: Adult Educational Attainment by Neighborhood Socioeconomic Status (SES) in 1990
Note: The solid red lines show local linear regressions of the share of tract residents with at least a high school diploma (light red) or at least a BA degree (dark red). Adult educational attainment is measured in the 1990 US Census as the share with at least a high school diploma (HS) or at least a BA (BA) for persons 25 years and over. Neighborhood SES is measured for same population in 1990 via the 1990 US Census.

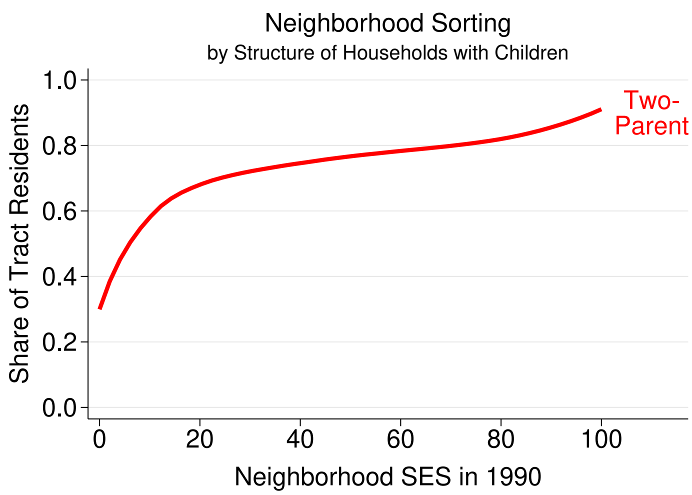


Figure 2: Household Structure by Neighborhood Socioeconomic Status (SES) in 1990
Note: The solid red line shows a local linear regression of the share of tract households with children that have two parents as measured in the 1990 US Census. Neighborhood SES is measured for households with children in 1990 via the 1990 US Census.

B More on Variation in Neighborhood SES from Housing Mobility Programs

Figures 3, 4, and 5a are reproduced from Aliprantis et al. (2024).

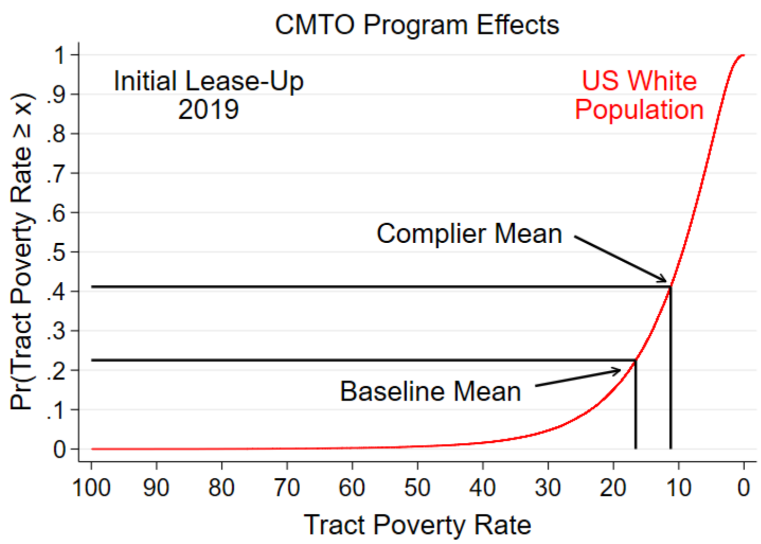


Figure 3: Creating Moves to Opportunity (CMTO)
Note: This figure displays, in red, the Cumulative Distribution Function of tract-level non-poverty for the United States' population of non-Hispanic whites in the 2014-2018 American Community Survey/NHGIS. The figure also shows the baseline mean and treatment group complier mean for CMTO participants in April 2019, where the complier mean is calculated as the control mean plus the treatment on the treated (TOT) effect.

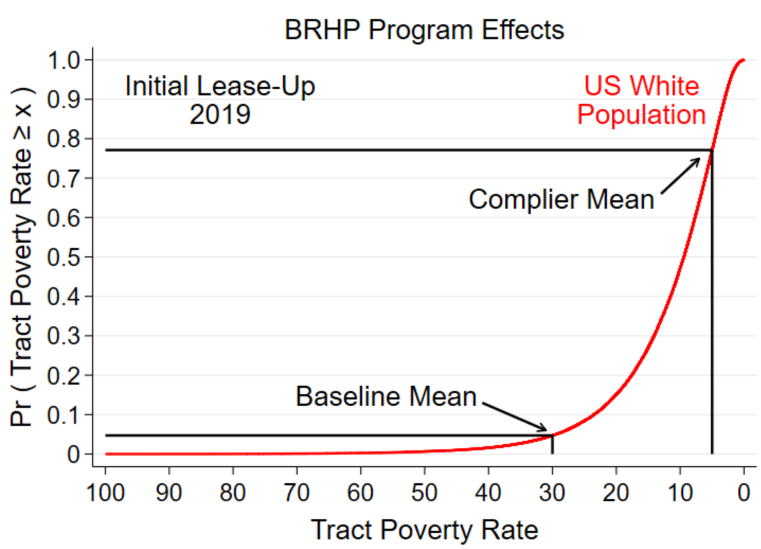
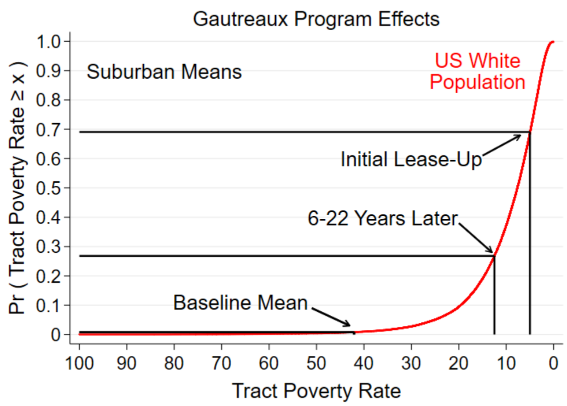
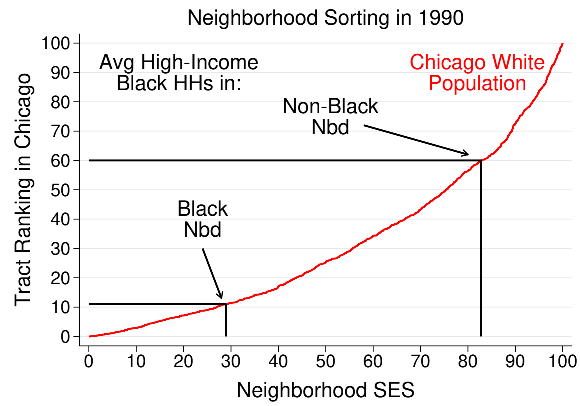


Figure 4: The Baltimore Regional Housing Partnership (BRHP)
Note: This figure displays, in red, the Cumulative Distribution Function of tract-level non-poverty for the United States' population of non-Hispanic whites in the 2014-2018 American Community Survey/NHGIS. The figure also shows the pre-program and post-move means of BRHP program participants in 2019.



(a) Gautreaux



(b) Chicago

Figure 5: Gautreaux and Race-Based Sorting in Chicago
Note: Panel a shows mean neighborhood poverty rates for the Gautreaux program taken from Table 1 of Keels et al. (2005) in terms of the 2000 Census distribution of the US non-Hispanic white population. Panel b shows the neighborhood SES of Black households in the top quintile of the overall US household income distribution.

C Data: Additional Details and Robustness

C.1 Measuring the Income Distribution

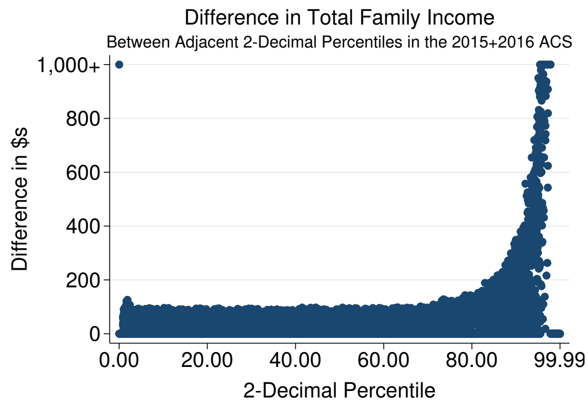


Figure 6: Assigning Income to Percentiles in the 2015 and 2016 Waves of the ACS

C.2 Public Use Microdata Areas (PUMAs)

While broader use of individual-level data would greatly facilitate the estimation of our model, the problems for interpretation are too large. For example, we could estimate the model using the US Census data provided by IPUMS USA (Ruggles et al. (2024)) that contains individual-level variables such as parental income, education, and household structure. However, the finest level of geography in the publicly-available IPUMS USA data is the Public Use Microdata Areas (PUMAs) of respondents. PUMAs typically contain about 100,000 residents, as compared to the 4,000 residents typically found in Census tracts. Appendix C.3 shows that about 40-50 percent of the tract-level variation in neighborhood SES is within PUMA. Moreover, Appendix C.3 shows that even at this much larger geography, neighborhood sorting by race in the US is so strong that the problem pointed out at the tract-level in Aliprantis et al. (2024) remains: there are many high-SES locations where we simply have not observed any Black boys grow up.

The US Census data provided by IPUMS USA (Ruggles et al. (2024)) contains individual-level variables such as parental income, education, and household structure. However, the finest level of geography in the publicly-available IPUMS USA data is the Public Use Microdata Area (PUMA) of respondents. PUMAs typically contain about 100,000 residents, as compared to the 4,000 residents typically found in Census tracts. A national regression of tract-level neighborhood SES on indicator variables for PUMAs in the 2010 data yields an R^2 of 0.24. While such a regression yields values of R^2 closer to 0.50 or 0.60 within specific metros, we use aggregated, tract-level data rather than individual-level data in our analysis to avoid using PUMAs to define neighborhoods.

Figure 7 provides an illustrative example showing the variation in tract-level SES within three PUMAs in Chicago in the 2010 Census. We see that PUMA 3203 has relatively uniformly high SES. However, neighborhood SES is almost uniformly distributed among the tracts in PUMA 3407, and PUMA 3207 also displays a very high level of dispersion.

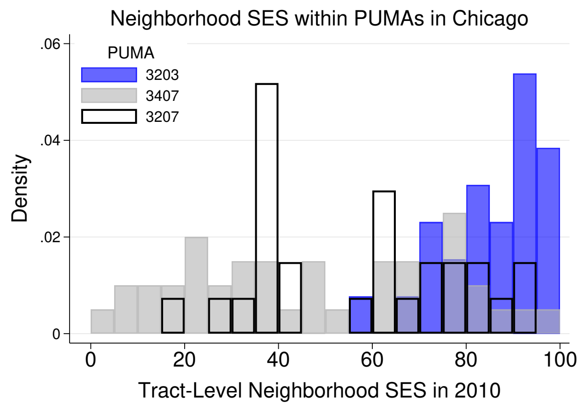
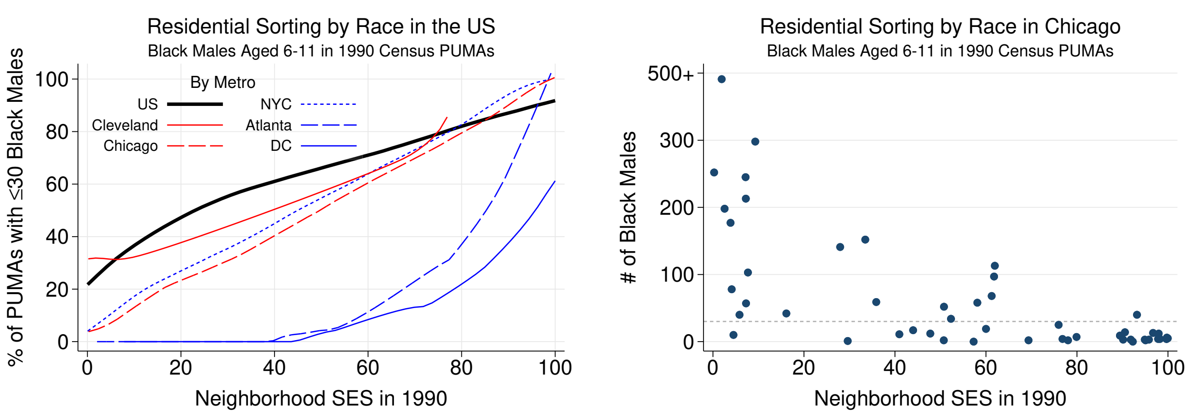


Figure 7: Within-PUMA Variation in Tract-Level Neighborhood SES

Moreover, even at the much larger geography of PUMAs, neighborhood sorting by race in the US is so strong that the problem at the tract level discussed in the text and originally noted in Aliprantis et al. (2024) remains: there are many high-SES locations where we simply have not observed any Black boys grow up.



(a) The US and Select Metros

(b) Chicago

Figure 8: Residential Sorting by Race in the United States and Chicago

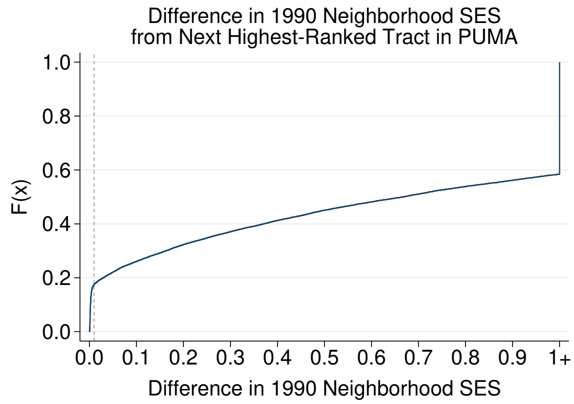
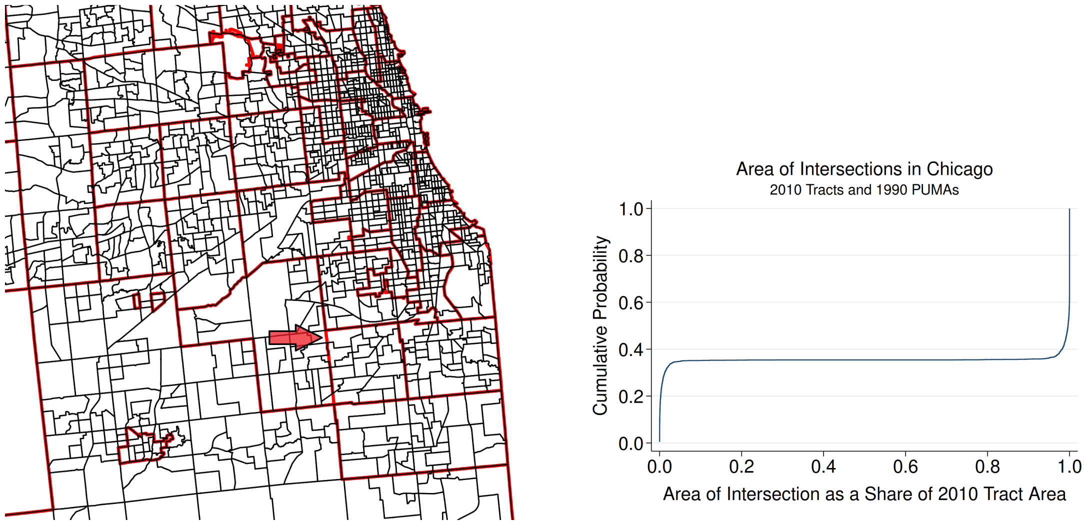


Figure 9: Within-PUMA Differences in Tract Rankings

C.3 1990 PUMA and 2010 Tract Boundaries

The 1990 PUMA boundaries were not drawn to coincide with other administrative boundaries, including tracts or counties. As a result, we use QGIS to intersect 1990 PUMAs with 2010 tracts. The 1990 PUMA shapefiles are the 2000 TIGER/Line Basis versions of the 5% State Sample downloaded from IPUMS USA and the 2010 tract shapefiles downloaded from the NHGIS. Below, Figure 10a shows that the boundaries of 1990 PUMAs and 2010 tracts coincide in most cases in Chicago. A pointer illustrates the rare cases when the boundaries do not coincide.

Figure 10b remains focused on Chicago to more formally quantify the coincidence of the boundaries of 1990 PUMAs and 2010 tracts. The figure shows the distribution of intersections between these geographies where each intersection is measured in terms of its area as a share of the corresponding 2010 tract's area. Figure 10b confirms the intuition garnered from looking at the map in Figure 10a; in most cases, nearly all of a tract is contained in one PUMA. There are a few places where a very small fraction of a tract will intersect with a PUMA, but it is extremely rare for a tract to be split relatively evenly between two PUMAs. In Chicago, for example, there are 3,422 intersections between 1990 PUMAs and 2010 tracts. Among those intersections, only 20 represent between 10 and 90 percent of the total area of the 2010 tract, which is 0.6 percent of the intersections. Thus, it is reasonable to follow a decision rule assigning a 2010 tract to the 1990 PUMA where most of it is contained.



(a) 1990 PUMAs (Red) and 2010 Tracts (Black) in Chicago

(b) Distribution of Intersection Sizes

Figure 10: Boundary Intersections between 2010 Tracts and 1990 PUMAs

C.4 Estimation Sample

We estimate the model using the 19 largest CBSAs in 1990 as ranked by the number of Black residents. These are New York City, Chicago, DC, Los Angeles, Philadelphia, Detroit, Atlanta, Miami, Houston, Baltimore, Dallas, New Orleans, Memphis, St. Louis, San Francisco, Virginia Beach, Cleveland, Charlotte, Richmond, and Birmingham. Figure 11 shows the number of Black residents by metro in 1990.

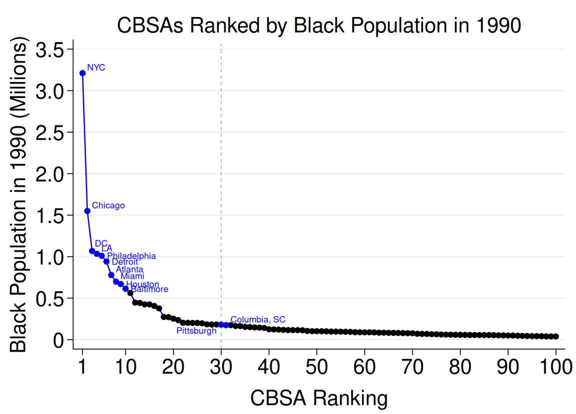
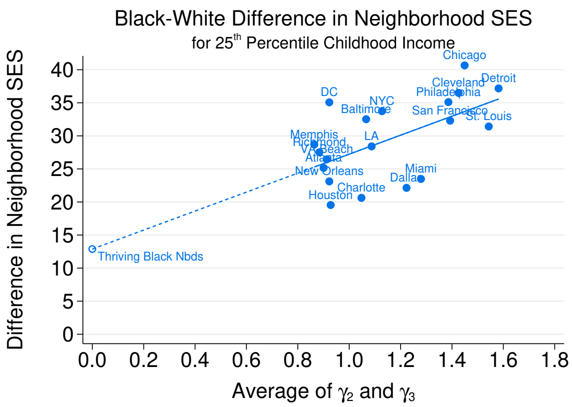
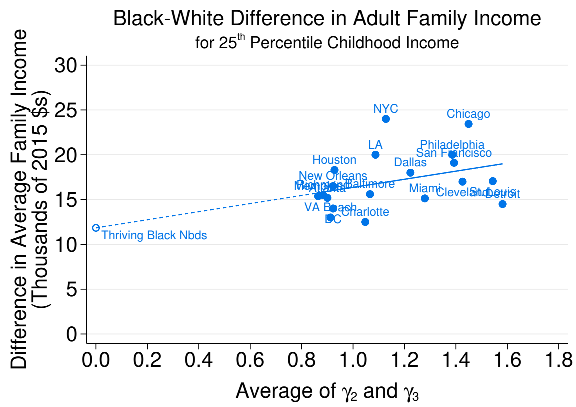


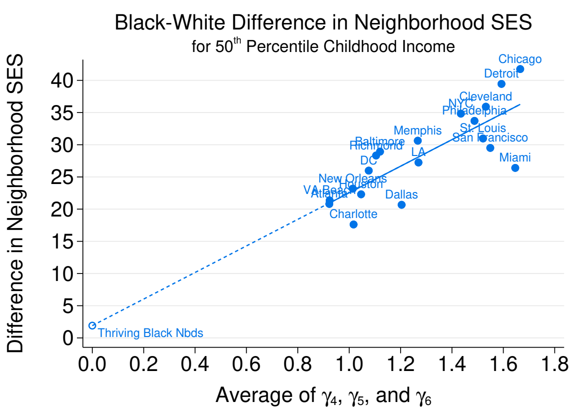
Figure 11: Black Population by CBSA in 1990



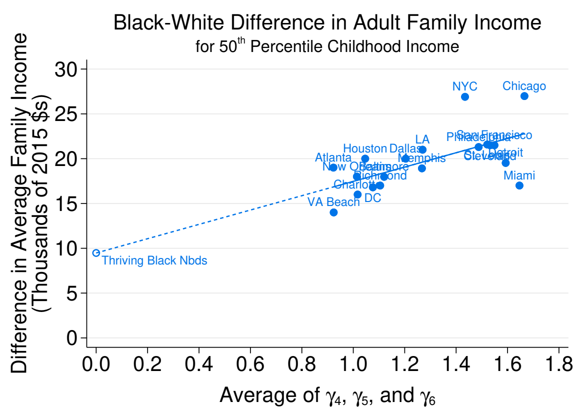
(a) Differences in Treatment at 25th Percentile



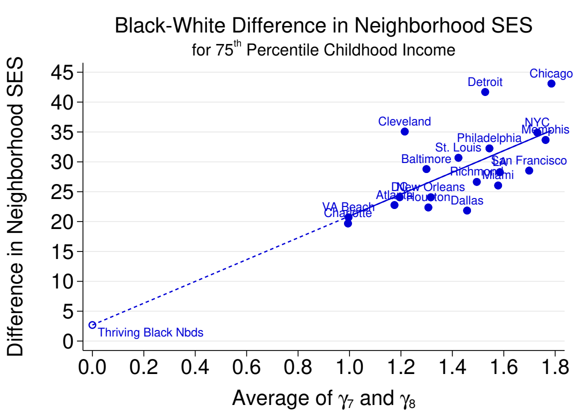
(b) Differences in Outcomes at 25th Percentile



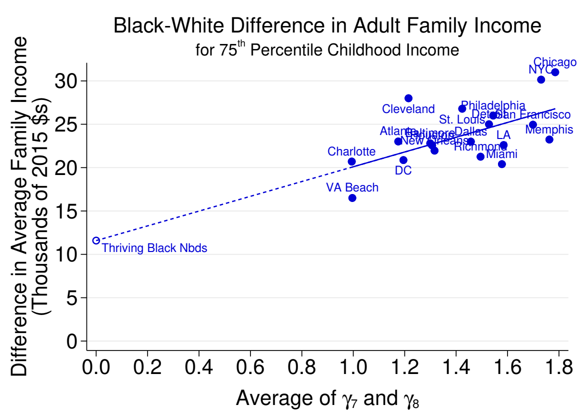
(c) Differences in Treatment at 50th Percentile



(d) Differences in Outcomes at 25th Percentile



(e) Differences in Treatment at 75th Percentile



(f) Differences in Outcomes at 75th Percentile

Figure 12: Differences in Childhood Treatment and Adult Outcomes by Metros' Estimated Cost γ of Accessing a Black Neighborhood

Appendix References

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