

Race and Economic Opportunity in the United States: An Intergenerational Perspective*

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Abstract

We study the sources of racial and ethnic disparities in income using de-identified longitudinal data covering nearly the entire U.S. population from 1989-2015. We document three sets of results. First, the intergenerational persistence of disparities varies substantially across racial groups. For example, Hispanic Americans are moving up significantly in the income distribution across generations because they have relatively high rates of intergenerational income mobility. In contrast, black Americans have substantially lower rates of upward mobility and higher rates of downward mobility than whites, leading to large income disparities that persist across generations. Conditional on parent income, the black-white income gap is driven entirely by large differences in wages and employment rates between black and white men; there are no such differences between black and white women. Second, differences in family characteristics such as parental marital status, education, and wealth explain very little of the black-white income gap conditional on parent income. Differences in ability also do not explain the patterns of intergenerational mobility we document. Third, the black-white gap persists even among boys who grow up in the same neighborhood. Controlling for parental income, black boys have lower incomes in adulthood than white boys in 99% of Census tracts. Both black and white boys have better outcomes in low-poverty areas, but black-white gaps are *larger* on average for boys who grow up in such neighborhoods. The few areas in which black-white gaps are relatively small tend to be low-poverty neighborhoods with low levels of racial bias among whites and high rates of father presence among blacks. Black males who move to such neighborhoods earlier in childhood earn more and are less likely to be incarcerated. However, fewer than 5% of black children grow up in such environments. These findings suggest that reducing the black-white income gap will require efforts whose impacts cross neighborhood and class lines and increase upward mobility specifically for black men.

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I Introduction

Racial disparities are among the most visible and persistent features of American society. For example, in 2016, the median household income of black Americans was \$39,500, compared with \$65,000 for non-Hispanic white Americans (U.S. Department of Commerce, Bureau of the Census 2017). The sources of these disparities have been heavily studied and debated, with proposed explanations ranging from residential segregation (e.g., Wilson 1987; Massey and Denton 1993) and discrimination (e.g., Pager 2003; Eberhardt et al. 2004; Bertrand and Mullainathan 2004) to differences in family structure (e.g., McAdoo 2002; Autor et al. 2016) and even genetics (e.g., Rushton and Jensen 2005).

Prior empirical research on racial disparities has typically tested competing theories using cross-sectional data that provide snapshots of individuals at a point in time.¹ In this paper, we analyze the sources of racial disparities from an intergenerational perspective, focusing on the dynamics of income across generations.² In canonical intergenerational models of inequality (e.g., Becker and Tomes 1979), racial differences in income distributions in the long run are determined by the magnitude of *intergenerational gaps*, e.g. the difference between black and white children’s incomes conditional on parent income. If black and white children have the same income distributions conditional on parental income, income disparities between the two groups would vanish in the long run regardless of their initial magnitude. From this perspective, the critical question to understand the black-white gap in the long run is: do black children have lower incomes than white children conditional on parental income, and if so, how can we reduce these intergenerational gaps?

We study this question using newly-available longitudinal data from the U.S. Census Bureau

¹There are three primary exceptions to this characterization of the prior literature, each of which addresses the lack of historical data linking parents to children in different ways: (1) studies that focus on intermediate outcomes such as test scores using data from schools, which contain information on parental income and other characteristics (e.g., Jencks and Phillips 1998; Magnuson and Duncan 2006; Fryer and Levitt 2006); (2) studies that use ethnographic methods (e.g., Carter 2005, Lareau 2011); and (3) work using longitudinal survey data, dating to Blau and Duncan (1967) and most importantly a recent set of papers by Mazumder and collaborators (e.g., Bhattacharya and Mazumder 2011; Mazumder 2014; Mazumder and Davis 2018) whose aggregate estimates of mobility by race are broadly consistent with ours. Relative to these studies, our study advances the literature by (1) directly examining long-term outcomes of interest, such as earnings, which turn out to exhibit patterns different from test scores; (2) presenting quantitative evidence that complements qualitative case studies; and (3) presenting evidence from population-level data that reveals several results that cannot be detected in survey data.

²We focus on five racial and ethnic groups – non-Hispanic whites, non-Hispanic blacks, non-Hispanic Asians, non-Hispanic American Indians and Alaskan Natives, and Hispanics – who together comprise 98.4% of individuals with non-missing race information for the children we study. As has been noted in prior work, there is considerable heterogeneity in outcomes within these five groups, and we caution that our conclusions should not be interpreted as applying uniformly to all subgroups within each of these populations. For simplicity, we use “race” to refer to race and ethnicity; “American Indians” to refer to American Indians and Alaskan Natives; and “whites” to refer to non-Hispanic whites, “blacks” to refer to non-Hispanic blacks, etc.

that covers virtually the entire American population from 1989-2015. Building on work by Akee et al. (2017), we use de-identified data from the 2000 and 2010 decennial Censuses linked to data from federal income tax returns and the 2005-2015 American Community Surveys to obtain information on income, race, parental characteristics, and other variables. We focus on children in the 1978-1983 birth cohorts who were born in the U.S. or authorized immigrants who came to the U.S. in childhood. Our primary analysis sample consists of 20 million children, approximately 94% of the total number of children in the birth cohorts we study.

We divide our empirical analysis into four parts. In the first part, we characterize intergenerational gaps by race. We measure children’s incomes as their mean household income in 2014-15, when they are in their mid-thirties. We measure their parents’ income as mean household income between 1994 and 2000, when their children are between the ages of 11 and 22. Following Chetty et al. (2014), we measure intergenerational mobility using a rank specification. We rank children based on their incomes relative to all other children in the same birth cohort. Similarly, we rank parents of these children based on their incomes relative to all other parents with children in the same birth cohort. This rank-based approach is convenient from a statistical perspective because the conditional expectation of children’s mean ranks given their parents’ ranks is well approximated by a linear function in all the subgroups we study.

We find that intergenerational mobility and the persistence of disparities vary greatly across racial groups. White children born to parents at the 25th percentile of the income distribution reach the 45th percentile on average, while those born to parents at the 75th percentile reach the 60th percentile. Hispanic children with parents at the 25th and 75th percentiles reach the 43rd and 54th percentiles, respectively. Hence, the intergenerational gap between Hispanics and whites is 2 percentiles at the 25th percentile and 6 percentiles at the 75th percentile. Because of these modest intergenerational gaps, Hispanic Americans are moving up significantly in the income distribution across generations. For example, a model of intergenerational mobility analogous to Becker and Tomes (1979) predicts that the gap will shrink from the 22 percentile difference between Hispanic and white parents observed in our sample to 10 percentiles for their children and to 6 percentiles in steady state.

Asian children with parents at the 25th and 75th percentiles reach the 56th and 64th percentiles on average, respectively. The high earnings of low-income Asian children echo the widespread perception of Asians as a “model minority” (e.g., Wong et al. 1998). However, the exceptional outcomes of low-income Asian children are largely driven by first-generation immigrants. Restricting the sam-

ple to Asians whose mothers were born in the U.S., we find intergenerational gaps between Asians and whites of approximately 2 percentiles on average across the parental income distribution. The changing patterns of intergenerational mobility for Asians make it more difficult to predict the trajectory of their incomes, but Asians appear likely to remain at income levels comparable to or above white Americans in the long run.

In stark contrast to Hispanics and Asians, there are large intergenerational gaps between black and American Indian children relative to white children. Both blacks and American Indians have rank-rank mobility curves that are shifted down relative to whites across the entire parental income distribution by approximately 13 percentiles. This remains true even among children born to parents in the top 1 percent, implying that children born into high-income black families have substantially higher rates of *downward* mobility than whites across generations, consistent with Bhattacharya and Mazumder (2011). Indeed, a black child born to parents in the top quintile is roughly as likely to fall to the *bottom* family income quintile as he or she is to remain in the top quintile; in contrast, white children are nearly five times as likely to remain in the top quintile as they are to fall to the bottom quintile.

The large intergenerational gaps for blacks and American Indians relative to whites lead to disparities in earnings for these groups that persist across generations. In steady state, the gap in family income ranks between whites and American Indians is 18 percentiles, while the white-black gap in family income ranks is 19 percentiles. These values are very similar to the empirically observed gaps for children in our sample, suggesting that blacks and American Indians are currently close to their steady-state income distributions.³ This result implies that reducing racial disparities going forward will require reducing *intergenerational* gaps for blacks and American Indians. Transient programs that do not affect intergenerational mobility directly, such as temporary cash transfers, are insufficient to reduce black-white gaps in income ranks because income distributions will revert back to their steady-states in future generations. Instead, reducing racial disparities requires policies that reduce black-white gaps in children’s outcomes conditional on parental income, such as changes in human capital acquisition or childhood environment, consistent with the conclusions of Cameron and Heckman (2001).

³Bayer and Charles (2018) show that the percentile rank difference in individual income between black and white men has been stable for several decades, while Manduca (2018) shows that the rank difference in household income between blacks and whites has narrowed in recent decades. Our analysis does not make predictions about historical trends in black-white gaps. Our point is simply that the gaps in household income ranks observed for the current generation are close to their steady-state values given currently observed levels of intergenerational mobility, consistent with the findings of Mazumder (2014).

In light of this finding, the rest of the paper focuses on understanding the factors that drive intergenerational gaps in income, particularly between blacks and whites.⁴ One mechanical explanation for black-white gaps in household income is that blacks marry at much lower rates than whites (Raley et al. 2015), leading to lower levels of household income simply because they tend to have one rather than two earners in their families. In the second part of the paper, we evaluate the role of marriage by measuring children’s incomes at the *individual* rather than the household level. We find significantly smaller black-white intergenerational gaps in individual income, of approximately 5 percentiles instead of 13 percentiles.

The reduction in the intergenerational gap when focusing on children’s individual incomes, however, masks important heterogeneity by gender. The intergenerational gap in individual income is 10 percentiles for black men across the parental income distribution – similar to the overall gap in family income. In contrast, black women earn about 1 percentile *more* than white women conditional on parent income. Moreover, there is little or no gap in wage rates or hours of work between black and white women, weighing against the hypothesis that black women have comparable incomes to white women simply because they work longer hours to compensate for lower levels of spousal income. Black men, by contrast, have substantially lower employment rates and wage rates than white men, even conditional on parental income. We find analogous gender differences in other outcomes as well: black-white gaps in high-school dropout rates, college attendance rates, occupation, and incarceration are all substantially larger for men than for women. Black women have higher college attendance rates than white *men*, conditional on parental income. For men, the gap in incarceration is particularly striking: 21% of black men born to the lowest-income families are incarcerated on a given day.

Given these results, we concentrate on understanding the sources of intergenerational gaps between black and white men in the rest of our analysis.⁵ We evaluate a wide range of theories of racial disparities, which we group into two categories: factors that vary at the family level (e.g., family structure or wealth) and factors that vary at the neighborhood level (e.g., the quality of

⁴We focus primarily on the black-white gap because of its size and persistence and because the large number of black individuals permits richer statistical analyses of mechanisms driving the gap than for other subgroups (e.g., American Indians).

⁵The lack of intergenerational gaps in individual income between black and white women does not mean that their incomes will converge in steady state, because black women still have lower family income than white women (due to lower marriage rates and spousal income). Insofar as children’s incomes depend upon the incomes of both of their parents, intergenerational gaps between black and white men will also generate a black-white gap in individual income for women in steady state. It follows that closing the intergenerational gap between black and white men would close the black-white gap in individual income not just for men but for women as well in steady state.

schools or social capital).⁶

In the third part of the paper, we evaluate family-level factors by conditioning on various parental characteristics. We begin by evaluating the hypothesis that the black-white gap is driven by the fact that black children are much more likely to be raised in single-parent families than white children. We find that controlling for parental marital status reduces black-white intergenerational gaps only slightly, from 10 percentiles to 9.3 percentiles. Under the natural assumption that other unobserved factors that contribute positively to childhood development are positively correlated with marital status, this finding suggests that parental marital status plays a limited role in explaining intergenerational gaps. Controlling for differences in parental education and wealth also does not affect the black-white intergenerational gap significantly. Put differently, when we compare the outcomes of black and white men who all grow up in two-parent families with similar levels of income, wealth, and education, we continue to find that the black men still have significantly lower incomes in adulthood.

The last family-level explanation we consider is the controversial hypothesis that differences in cognitive ability explain racial gaps. Although we do not have measures of ability in our data, three pieces of evidence suggest that differences in ability do not explain the persistence of black-white gaps for men. First, the prior literature (e.g., Rushton and Jensen 2005) suggests no biological reason that racial differences in cognitive ability would vary by gender. Therefore, the ability hypothesis does not explain the differences in black-white income gaps by gender. Second, black-white gaps in test scores – which have been the basis for most prior arguments for ability differences – are substantial for *both* men and women. The fact that black women have incomes and wage rates comparable to white women conditional on parental income despite having much lower test scores suggests that tests do not accurately measure differences in ability (as relevant for earnings) by race, perhaps because of stereotype threat or racial biases in tests (Steele and Aronson 1995; Jencks and Phillips 1998). Third, we show below that environmental conditions during childhood have *causal* effects on racial disparities by studying the outcomes of boys who move between neighborhoods, rejecting the hypothesis that the gap is driven by differences in innate ability.

Given that differences in family characteristics explain relatively little of the black-white gap, in the last part of the paper we examine environmental factors that extend beyond the family

⁶There is a voluminous literature assessing each of these explanations. Altonji and Blank (1999) and Fryer (2010) provide comprehensive surveys of the economics and education literatures. Sampson et al. (2002a) and Small and Lamont (2010) summarize work in sociology on neighborhood effects and culture. See Online Appendix Table I for a more detailed categorization of alternative explanations and selected references.

by studying variation across neighborhoods. We begin by assessing the role of regional factors by analyzing the geography of intergenerational mobility for blacks and whites, disaggregating Chetty et al.’s (2014) analysis by race. We find significant heterogeneity in children’s outcomes conditional on parental income across areas, but there are substantial black-white gaps in nearly every commuting zone (CZs). Areas that have higher rates of upward mobility for whites tend to have higher rates of upward mobility for blacks as well. For both blacks and whites, rates of upward mobility are highest for children who grow up in the Great Plains and the coasts and lowest in the cities in the industrial Midwest. One notable exception to this pattern is the Southeast, where whites have especially low rates of upward mobility but blacks do not.

Next, we zoom in to narrower geographies, as in prior sociological work studying neighborhood effects within specific cities (e.g., Sampson et al. 1997; Sharkey 2013). We find large intergenerational gaps even between black and white men who grow up in the same Census tract (containing 4,256 people on average) or block (containing 50 people on average). Among children with parents at the 25th percentile, black boys have lower incomes in adulthood than white boys in 99% of Census tracts. The mean intergenerational gap in individual income ranks between black and white boys with parents at the 25th percentile remains at 7.7 percentiles with tract fixed effects and 7.0 percentiles with block fixed effects. Hence, the intergenerational gap would fall by at most 25% if black and white boys were to grow up in the same neighborhoods.

The fact that neighborhood differences explain relatively little of the black-white gap does not mean that neighborhoods do not matter for children’s outcomes. Consistent with prior work on neighborhood effects (e.g., Chetty et al. 2016), we find substantial variation across neighborhoods in both black and white boys’ outcomes. Both black and white boys have significantly higher incomes if they grow up in neighborhoods that are typically perceived to be “good” areas: for instance, tracts with low poverty rates, high test scores, or a large fraction of college graduates. However, black-white gaps are *larger* on average for boys who grow up in such neighborhoods because the correlation between growing up in a good (e.g., low-poverty) area and income is greater for white boys than black boys.

Among low-poverty neighborhoods (those with poverty rates below 10%), there are two factors that are strongly associated with better outcomes for black men and *smaller* black-white gaps: low levels of racial bias among whites and high rates of father presence among blacks. Within low-poverty areas, black men who grow up in tracts with greater racial bias among whites – measured using tests for implicit bias or indices of explicit racial animus based on Google searches – earn less

and are more likely to be incarcerated. Greater racial bias is correlated with worse outcomes for black boys even conditional on state fixed effects. The fraction of fathers present in the neighborhood – defined as being claimed as a child dependent by a male on tax forms – among low-income black households is associated with better outcomes among black boys, but is uncorrelated with the outcomes of black girls and white boys. Black father presence at the neighborhood level strongly predicts black boys’ outcomes irrespective of whether their own father is present or not, suggesting that what matters is not parental marital status itself but rather community-level factors, echoing the findings of Sampson (1987).

Finally, building on the methodology of Chetty and Hendren (2018a), we show that black boys who move to better areas (as measured by the outcomes of other black residents) earlier in their childhood have higher incomes and lower rates of incarceration in adulthood. These childhood exposure effects are race-specific: black movers’ outcomes are predicted by the outcomes of other black residents, but not white residents. These findings show that environmental conditions during childhood have *causal* effects on racial disparities, demonstrating that the black-white income gap is not immutable.⁷

We conclude that neighborhoods with low poverty rates, high rates of father presence among blacks, and low levels of racial bias among whites have better outcomes for black boys and smaller racial gaps. But very few black children currently grow up in such environments. Less than 5% of black children currently grow up in areas with a poverty rate below 10% and more than half of black fathers present. In contrast, 63% of white children live in areas with poverty rates below 10% and more than half of white fathers present. Importantly, these differences in childhood environment arise not just from factors that vary across neighborhoods, such as poverty rates or the quality of schools. Factors that affect racial groups differentially *within* neighborhoods – such as rates of father presence, the degree of racial bias, or perhaps segregation by race within neighborhoods – also matter. Thus, our findings suggest that reducing the intergenerational persistence of the black-white income gap will require policies whose impacts cross neighborhood and class lines and increase upward mobility specifically for black men.

The rest of this paper is organized as follows. Section II presents a stylized model of intergenerational mobility and racial disparities that we use to organize our empirical analysis. Section

⁷As is now conventional in much of the social sciences, we use a potential outcomes framework (Neyman 1923; Holland 1986) to define notions of causality. We identify causal effects of neighborhoods under the identification assumption described in Chetty and Hendren (2018a) and discussed below in Section VII.C. However, we emphasize that the correlations with neighborhood characteristics we document are associations that should not be interpreted as causal effects.

III describes the data. In Section IV, we characterize intergenerational mobility by race. Section V examines the role of differences in marriage rates and heterogeneity by gender in black-white gaps. Section VI analyzes how family-level factors affect intergenerational gaps, while Section VII focuses on environmental factors by examining variation across neighborhoods. Section VIII concludes. Supplementary results and methodological details are provided in an online appendix. Statistics on children’s outcomes by race, parental income, and other characteristics are available at the commuting zone level on the Equality of Opportunity Project [website](#).

II Conceptual Framework

We structure our empirical analysis using a stylized statistical model of income inequality and intergenerational mobility, building upon Becker and Tomes (1979). We use the model to identify the parameters that control the evolution of racial disparities.

Consider a discrete-time setting in which t indexes generations. For simplicity, assume that each family, indexed by i , consists of a single individual in each generation t .⁸ Let y_{it} denote the income percentile rank of individual i relative to all other individuals in the same generation t , and let $r(i)$ denote the race of family i .⁹ We show in our empirical analysis that the conditional expectation of children’s mean ranks given their parents’ ranks is approximately linear for all races. We therefore model individual i ’s income as a race-specific linear function of his or her parents’ income:

$$y_{it} = \alpha_r + \beta_r y_{i,t-1} + \varepsilon_{it}, \quad (1)$$

where ε_{it} denotes an idiosyncratic shock that is independent across generations and has expectation $E[\varepsilon_{it}] = 0$. In Chetty et al.’s (2014) terminology, $\alpha_r \in [0, 1]$ measures *absolute* rank mobility for children of the lowest-income parents: the mean rank of a child of race r whose parents have income rank $y_{i,t-1} = 0$. The parameter $\beta_r \in [0, 1]$ measures the rate of *relative* mobility: the association between the mean percentile rank of children and their parents’ income ranks for race r . We assume that α_r and β_r do not vary across generations. Chetty et al. (2014) present evidence in support of this assumption pooling races for recent cohorts, and we present further evidence supporting this

⁸We discuss an extension of the model in which men and women have different incomes that depend upon their mothers’ and fathers’ incomes in Section V.

⁹By focusing on percentile ranks, we capture changes in the relative position of racial groups in the income distribution. As discussed in Bayer and Charles (2018) and Manduca (2018), trends in the absolute dollar magnitude of racial disparities depend upon both changes in ranks and the marginal distribution of income in each generation. We focus on ranks to separate the forces that affect racial disparities from forces that affect the income distribution more generally, such as skill-biased technical change. The rank-based estimates of mobility we report here can be translated into dollar gaps using the methods in Chetty et al. (2017).

assumption by race in Online Appendix Table IX.

Under the linear specification in (1), one does not need to track the evolution of the full income distribution to characterize the evolution of mean outcomes by race. The mean rank of individuals of race r in generation t is simply $\bar{y}_{rt} = \alpha_r + \beta_r \bar{y}_{r,t-1}$. Iterating over generations, we can write the mean rank in generation $t + s$, $\bar{y}_{r,t+s}$, as a function of the mean rank in generation t , \bar{y}_{rt} :

$$\bar{y}_{r,t+s} = \alpha_r \frac{1 - \beta_r^s}{1 - \beta_r} + \beta_r^s \bar{y}_{rt}. \quad (2)$$

As $s \rightarrow \infty$, $\beta_r^s \rightarrow 0$ if $\beta_r < 1$. Hence, the mean rank of individuals of race r converges in the long run to a steady-state in which

$$\bar{y}_{rt} = \bar{y}_{r,t-1} = \bar{y}_r^{SS} = \frac{\alpha_r}{1 - \beta_r}. \quad (3)$$

We now turn to the implications of (2) and (3) for the evolution of racial disparities. Let $\Delta \bar{y}_t = \bar{y}_{r_1 t} - \bar{y}_{r_2 t}$ denote the mean gap between two races r_1 and r_2 in generation t . For expositional convenience, we consider a series of cases of increasing generality.

Constant Relative and Absolute Mobility. We begin with the case in which absolute and relative rates of intergenerational mobility do not vary by race: $\alpha_r = \alpha$ and $\beta_r = \beta$ for all r . In this case, the racial gap in mean ranks in steady state is $\Delta \bar{y}^{SS} = 0$, as all races converge to the same mean rank, irrespective of their initial conditions \bar{y}_{r0} . The gap in generation $t + s$ is $\Delta \bar{y}_{t+s} = \beta^s \Delta \bar{y}_t$. As noted by Becker and Tomes (1979), the rate of convergence in incomes across racial groups is determined by the rate of relative mobility β . Chetty et al. (2014) estimate that $\beta \simeq 0.35$ pooling all races in the U.S. This level of relative mobility implies that racial disparities would fall to 35% of their current level after one generation and just 12% of their current level after two generations, as illustrated in Figure Ia. In the absence of differences in intergenerational mobility by race, racial disparities in income would dissipate relatively rapidly across generations given observed levels of mobility and vanish entirely in steady-state.

Constant Relative Mobility. Next, consider the case where absolute mobility varies by race, but relative mobility does not: $\beta_r = \beta$. Let $\Delta \alpha = \alpha_w - \alpha_b$ denote the racial difference in absolute mobility, i.e. the expected gap in children's ranks conditional on parental income, which we term the *intergenerational gap*. In this case, the racial gap in steady-state is

$$\Delta \bar{y}^{SS} = \frac{\Delta \alpha}{1 - \beta}.$$

The steady-state disparity is directly proportional to the size of the intergenerational gap $\Delta \alpha$, as shown in Figure Ib. Reducing racial disparities in the long run therefore requires reducing

intergenerational gaps. Reducing the current gap $\Delta\bar{y}_0$ without changing $\Delta\alpha$ will not affect racial disparities in the long run.

The gap in generation $t + s$ is

$$\Delta\bar{y}_{t+s} = (1 - \beta^s)\Delta\bar{y}^{SS} + \beta^s\Delta\bar{y}_t. \quad (4)$$

The gap in generation t is given by a weighted average of the steady-state gap and the current gap, with the weight determined by the rate of relative mobility β . As discussed above, if $\beta = 0.35$ as observed empirically, convergence to the steady-state is relatively rapid and hence what matters most even after one or two generations is primarily the intergenerational gap $\Delta\alpha$.

The difference between the racial gap in the current generation and the steady state, $\Delta\bar{y}_t - \Delta\bar{y}^{SS}$, measures the extent to which current disparities are driven purely by intergenerational gaps ($\Delta\alpha$) versus historical factors ($\Delta\bar{y}_0$). If $\Delta\bar{y}_t - \Delta\bar{y}^{SS}$ is small, we can infer (under our assumption that rates of intergenerational mobility are stable) that most of the current disparity is due to intergenerational gaps rather than transitory factors.

General Case. We now return to the general case in which both α_r and β_r vary across races. Here, steady-state disparities and rates of convergence are determined by the race-specific rates of relative and absolute mobility. As noted above, prior work has established that the average level of β pooling all races is approximately 0.35 in the U.S., but there is less evidence on how β_r varies by race (Mazumder 2014). Estimating β_r by race is important because groups that have low relative mobility (high β_r) could remain stuck at lower income levels for many generations even in the absence of steady-state gaps. For example, suppose whites and blacks have the same steady-state mean rank and that whites are currently in steady-state, but blacks are not. In this case, the gap in period $t + s$ is $\Delta\bar{y}_{t+s} = \beta_b^s\Delta\bar{y}_t$, where β_b denotes relative mobility for blacks. If $\beta_b = 0.75$, it would take 8 generations for the black-white disparity $\Delta\bar{y}_0$ to fall to 10% of its current level.

To summarize, race-specific rates of relative and absolute mobility (α_r, β_r) control the persistence of racial disparities and can provide guidance on the types of interventions that may be most effective in reducing disparities. If relative mobility is high for all races (low β_r), reducing racial disparities requires policies that reduce racial gaps in children's outcomes *conditional* on parental income ($\Delta\alpha$), perhaps through changes in schooling or childhood environment. Transitory interventions, such as temporary cash transfers targeted by race, will have limited long-run effects unless they change the process of intergenerational mobility itself. In contrast, if racial disparities emerge from low rates of relative mobility (high β_r) combined with large gaps due to historical or transient

factors (high $\Delta\bar{y}_t$), then temporary interventions or policies that increase relative mobility would have more persistent effects.

The result that convergence rates and steady-state income distributions are determined purely by rates of intergenerational mobility at the individual level holds only under the assumptions of our stylized model. In richer models that permit children’s outcomes to depend upon other factors beyond their parents’ incomes (e.g., their community’s incomes or their grandparents’ incomes) or allow for features such as assortative mating, interracial marriage, and endogenous fertility, steady-state outcomes and convergence rates will depend upon other parameters as well (e.g., Borjas 1992). However, racial disparities are still influenced by intergenerational gaps in these more general models. Hence, the simple framework outlined here provides a useful way to organize our empirical analysis and make qualitative predictions about the evolution of disparities across generations, but the quantitative predictions regarding steady states reported below must be interpreted with caution.

Motivated by this framework, we focus on two sets of questions in our empirical analysis. First, how do rates of intergenerational mobility vary across racial groups and what fraction of current racial disparities are due to persistent vs. transitory factors? Second, what factors lead to differences in intergenerational mobility by race and produce gaps that persist across generations?

III Data

We combine two sources of data housed at the Census Bureau in our primary analysis: data from the Census 2000 and 2010 short forms and data drawn from federal income tax returns in 1989, 1994, 1995, and 1998-2015. For certain supplemental analyses, we also use data from the Census 2000 long form and the 2005-2015 American Community Surveys (ACS). The Census short forms are designed to cover the entire population; the Census 2000 long form is a stratified random sample covering approximately one-sixth of households; and the American Community Survey is a stratified random sample covering approximately 2.5% of households in each year (U.S. Department of Commerce, Bureau of the Census 2000; U.S. Department of Commerce, Bureau of the Census 2003; U.S. Department of Commerce, Bureau of the Census 2014).

These datasets are linked by a unique person identifier called a Protected Identification Key (PIK) that is assigned by Census Bureau staff using information such as Social Security Numbers (SSN), names, addresses, and dates of birth. The Census Bureau uses the Numident, a dataset covering all SSN holders, and other administrative data to assign PIKs. All analysis in this paper

is conducted using a linked dataset that contains PIKs but is stripped of personally identifiable information.

The record linkage algorithm used to assign individuals PIKs is described in Wagner and Layne (2014). Using datasets that have both SSNs and other identifiers, Layne et al. (2014) show that the error rate in assigning PIKs when one does not have SSNs (as in Census surveys) is typically below 1% for government datasets. In the 2010 Census, 90.3% of individuals are successfully assigned a PIK (Wagner and Layne 2014, Table 2). Bond et al. (2014) show that PIK rates vary slightly across population subgroups in the 2010 ACS, but exceed 85% in virtually all subgroups. We present statistics on the fraction of our target population covered by our linked dataset below.

In the rest of this section, we describe how we construct our analysis sample, define the variables we use, and present summary statistics. Further details are given in Online Appendix A.

III.A Sample Definition

Our target sample frame consists of all children in the 1978-83 birth cohorts who were (1) born in the U.S. or are authorized immigrants who came to the U.S. in childhood and (2) whose parents were also U.S. citizens or authorized immigrants.¹⁰ We construct this sample frame in practice by identifying all children who were claimed as a child dependent on a 1040 tax form at some point between 1994-2015 by an adult who appears in the 2016 Numident file and was between the ages of 15-50 at the time of the child’s birth.¹¹ We then restrict the sample to children who were born between 1978-83, based on their record in the 2016 Numident. Note that this sample definition excludes children who are unauthorized immigrants or who are claimed as dependents by unauthorized immigrants because unauthorized immigrants do not have SSNs and therefore do not appear in the Numident file.

We define a child’s “parent” as the person who first claims the child as a dependent (between 1994-2015). This person must be supporting the child to claim him or her as a dependent, but may not necessarily be the child’s biological parent.¹² If the child is first claimed by a single filer, the child is defined as having a single parent. For simplicity, we assign each child a parent (or parents)

¹⁰We limit our analysis to individuals who are authorized immigrants because coverage rates of tax data for unauthorized immigrants are difficult to determine.

¹¹Dependent claiming information is not available in tax returns from 1989. We impose the 15-50 age restriction to limit links to grandparents or other guardians who might claim a child as a dependent.

¹²An alternative method of identifying parents is to use information on relationships to household members in the 2000 Census short form. We find that the tax- and Census-data based measures of parents are well aligned: for instance, among the children claimed as dependents by parents on a 1040 tax form in 2000, 93% live with the same parents in the 2000 Census. We use the tax data to identify parents because many of the children in the oldest cohorts in our sample have left their parents’ houses by the 2000 Census.

permanently using this algorithm, regardless of any subsequent changes in parents’ marital status or dependent claiming.

If parents never file a tax return, we do not link them to their child. Although some low-income individuals do not file tax returns in a given year, almost all parents file a tax return at some point between 1994 and 2015 to obtain a tax refund on their withheld taxes and the Earned Income Tax Credit (Cilke 1998). As a result, virtually all of the children in the 1978-83 birth cohorts are linked to parents (Online Appendix Table II). We limit our analysis to children born during or after 1978 because many children begin to leave the household starting at age 17 (Chetty et al. 2014, Appendix Table I) and the first year in which we have dependent claiming information is 1994.

In Online Appendix B, we assess the representativeness of our analysis sample by comparing sample counts and descriptive statistics to corresponding measures from the ACS. Our analysis sample covers approximately 94% of our target sample frame and has income distributions and demographic characteristics very similar to the ACS (Online Appendix Tables II-IV), confirming that it provides an accurate representation of our target population.

III.B Variable Definitions

In this subsection, we define the variables we use in our primary analysis. We measure all monetary variables in 2015 dollars, adjusting for inflation using the consumer price index (CPI-U).

Variable Definitions for Parents.

Income. Our primary measure of parent income is total pre-tax income at the household level, which we label parent family or household income.¹³ In years where a parent files a tax return, we define household income as Adjusted Gross Income (as reported on the 1040 tax return) plus tax-exempt interest income and the non-taxable portion of Social Security and Disability benefits. In years where a parent does not file a tax return, household income is coded as zero.¹⁴ Following Chetty et al. (2014), we define our baseline parental income measure as the mean of parents’ household income over five years: 1994, 1995, and 1998-2000, as tax records are unavailable in 1996 and 1997.¹⁵ We exclude children whose mean parent income is zero or negative (1.0% of children)

¹³We use the term “household” income for simplicity, but we do not include incomes from cohabitating partners or other household members aside from the primary tax filer’s spouse.

¹⁴Prior work (e.g., Chetty et al. 2014) has used information from W-2 forms to measure income for non-filers. We cannot follow that approach here since income data from W-2 forms are unavailable at the Census Bureau before 2005. However, this has little impact on results; Chetty et al. (2014) show that in 2000, the median W-2 income among parents who were non-filers was \$29, and only 2.9% of parents do not file in a given year. Information from W-2s is more important when measuring the incomes of children in early adulthood, for whom we do have W-2 data at the Census Bureau.

¹⁵Formally, we define mean household income as the mother’s individual income plus the father’s individual income

because parents who file tax returns (as is required to link them to a child) reporting negative or zero income typically have large capital losses, which are a proxy for having significant wealth.

Marital Status. We identify parents’ marital status based on their tax filing status in the year the child is first claimed as a dependent by parents. We say that a child has a “father present” if one of the tax filers who claims the child as a dependent in that year is male.

Educational Attainment. We obtain information on the highest level of education parents have completed from the American Community Survey and the 2000 Census long form, prioritizing information from the ACS (which is more recent) if both sources are available. We define “parental education” as the mother’s education if available; if not, we use the father’s education. We define seven categories of parental education: no school, less than a high school degree, high school degree, college with no degree, associate’s degree, bachelor’s degree, and post-graduate degree. Education (and all other variables obtained from the ACS or Census long form) are coded as missing for individuals who do not appear in the ACS or Census long form samples.

Wealth. We proxy for parents’ wealth (again, prioritizing the mother’s data) using information on home ownership, monthly mortgage payments, home value, and the number of vehicles from the 2000 Census long form and the ACS. A parent is a “home owner” if they report owning the home where they received the survey. Monthly mortgage payments and home values are self-reported by homeowners. Individuals who do not own a home are assigned a mortgage payment and home value of zero. The number of vehicles is defined as the number of vehicles used by members of the household.

Location. In each year, parents are assigned an address based on the address from which they filed their 1040 tax return. For non-filers, we use address information from information returns such as W-2s, which are available beginning in 2003.¹⁶ Addresses are coded as missing in years when a parent does not file or does not have an information return. For children whose parents were married when they were first claimed as dependents, we prioritize the mother’s location if marital status changes. Addresses are mapped to geographies such as Census tract or Census block using a geocoding algorithm developed by the Census Bureau (see Online Appendix A for details).

U.S. Native Status. Children are defined as having a “native-born” mother if their mother was in each year of 1994-95 and 1998-2000 divided by 10 (or divided by 5 if we only identify a single parent). For parents who do not change marital status, this is simply mean household income over the 5 year period. For parents who are married initially and then divorce, this measure tracks the mean household incomes of the two divorced parents over time. For parents who are single initially and then get married, this measure tracks individual income prior to marriage and total household income (including the new spouse’s income) after marriage.

¹⁶Address information from W-2s starts in 2003, but income amounts are not available until 2005.

surveyed in the 2000 Census long form or the ACS and reported being born in the United States in either survey.

Variable Definitions for Children.

Income. We define children’s annual household income in the same way as parents’ income except in our treatment of non-filers. Since W-2 data are available for the years in which we measure children’s incomes, we define income for a child who does not file a tax return as wage earnings reported on form W-2. We define children’s individual incomes as their own W-2 wage earnings plus self-employment and other non-wage income, which we define as Adjusted Gross Income minus total wages reported on form 1040 divided by the number of tax filers (thereby splitting non-wage income equally for joint filers). In years in which children have no tax return and no information returns, both individual and household income are coded as zero. We measure children’s individual and household incomes as their mean annual incomes in 2014 and 2015, when children are between the ages of 31 and 37.

Marriage. A child’s marital status is measured based on whether he or she files a tax return jointly in 2015.

Gender and Age. Gender and age are obtained from the Numident file.

Race. We assign race and ethnicity to children using the information they report on the 2010 Census short form. If the child’s PIK does not appear in the 2010 Census microdata, we use the 2000 Census short form; if the child does not appear in the 2000 Census, we then use the ACS. We aggregate race and ethnicity categories into a Hispanic ethnicity category and a set of non-Hispanic races: White, Black, Asian, American Indian or Alaskan Native, and Other, following the Office of Management and Budget (1997). Individuals who report two or more races are classified in the “Other” category.

Employment. We use two measures of employment, one based on the tax data and one based on the ACS. In the tax data, children are defined as working if they have non-zero individual income in either 2014 or 2015. In the ACS, children are defined as working if they report positive weeks worked in the past year. This and all other employment-related ACS measures described below are defined only among children who receive the ACS at age 30 or later.

Hours Worked. Annual hours worked are measured in the ACS as the product of hours worked per week and weeks worked per year. Individuals report weeks worked in bins; we use the midpoint of the bin to assign each individual a single value (e.g., those who choose “27 to 39 weeks” are assigned a value of 33). We convert the annual measures to average weekly hours worked by

dividing annual hours worked by 51 (the midpoint of the top bin of weeks worked). Those not working in any week are coded as having zero hours of work.

Hourly Wage. Hourly wages are measured in the ACS by dividing reported annual wage and salary income by annual hours worked. The hourly wage is coded as missing for those with zero hours worked.

Occupation. We obtain information on children’s occupations from the ACS for children who have positive hours worked.

Educational Attainment. We measure children’s educational attainment based on the highest level of education they report having completed in the ACS or the 2000 Census long form (prioritizing the ACS, since it is more recent). We say a student dropped out of high school if their educational attainment is “12th grade- no diploma” or less (hence, those with GEDs are not counted as having dropped out). We define college attendance as having obtained “at least some college credit.” When measuring high school completion, we require that individuals are at least 19 at the time they are surveyed; when measuring college attendance, we require that individuals are at least 20.

Incarceration. Using data from the 2010 Census short form, we define an individual as incarcerated on the day of the Census (April 1, 2010) based on whether he or she lives in any of the following types of group quarters: federal detention center, federal prison, state prison, local jail, residential correctional facility, military jail, or juvenile correctional facility.

Location. Children’s locations are measured based on the address from which they file tax returns in 2015. For non-filers, we obtain address information from W-2 forms and other information returns. If no address information is available in 2015, we use the most recent year in which an address is available.

III.C Summary Statistics

Table I and Online Appendix Tables V-VIII report summary statistics for children and parents, by race and gender. There are 21.3 million children in our analysis sample, of whom 94% have non-missing information on race (Online Appendix Table II). Of those with non-missing race information, 67% are white, 14% are black, 13% are Hispanic, 3% are Asian, and 0.8% are American Indian. The median household income among children in 2014-15 (between the ages of 31-37) is \$53,730 for whites, \$20,650 for blacks, \$35,180 for Hispanics, \$63,720 for Asians, and \$22,260 for American Indians. Among parents, median household income is \$70,640 for whites, \$29,200

for blacks, \$33,060 for Hispanics, \$53,010 for Asians, and \$34,850 for American Indians. These differences in household income are partly driven by differences in marriage rates: 79.3% of white children grow up in two-parent households, compared with 32.2% of black children. Other variables vary across the groups in a similar manner. Notably, 10.3% of black men in our sample of children were incarcerated on April 1, 2010 (between ages 27-32), a percentage far higher than for any of the other subgroups.

In Online Appendix B and Appendix Table IV, we show that income distributions measured in the tax records closely match those in the Current Population Survey and the ACS. For example, the median income in 2015 of children who appear in both our analysis sample and the 2015 ACS is \$33,370 based on the tax data, compared with \$34,000 based on the ACS data. Individuals recorded as having zero income in the tax records (because they do not file and have no W-2s) have a median income of \$5,000 in the ACS, showing that tax records do not miss substantial amounts of income for non-filers.

IV Intergenerational Mobility by Race

In this section, we characterize the evolution of racial disparities across generations using the framework in Section II. We begin by estimating relative and absolute intergenerational mobility (α_r, β_r) for each racial group using the specification in (1). Following Chetty et al. (2014), we measure parents' and children's incomes using percentile ranks. We rank children based on their incomes relative to all other children in the same birth cohort. Similarly, we rank parents based on their incomes relative to all other parents with children in the same birth cohort. Pooling all races, we obtain an estimate of relative mobility of $\beta = 0.35$ in our analysis sample (Online Appendix Figure I), very similar to the estimate of $\beta = 0.34$ reported by Chetty et al. (2014, Figure IIa) based purely on tax records.¹⁷

Blacks vs. Whites. Figure IIa plots the mean household income rank of children versus the household income rank of their parents, for black and white children. For whites, we estimate a slope (relative mobility) of $\beta_w = 0.32$: a 10 percentile increase in parents' rank is associated with a 3.2 percentile increase in children's rank on average. The intercept for whites is $\alpha_w = 36.8$; i.e., white children born to the lowest-income parents reach the 36.8th percentile on average. The relationship between children's expected ranks and parents' ranks is linear across almost the entire

¹⁷The estimate increases by 0.01 because we measure children's incomes at slightly older ages in this paper (ages 31-37 vs. ages 29-32), reducing the amount of lifecycle bias.

parental income distribution, but is convex in the upper tail (top 5%). Children from very high-income families have especially high incomes themselves; for instance, white children with parents at the 100th income percentile have a mean rank of 74.0.

Blacks have relative mobility comparable to whites ($\beta_b = 0.28$), but have uniformly lower rates of absolute mobility across the entire parental income distribution. For example, black children with parents at the 25th percentile reach an income rank of 32.6 on average, 12.6 percentiles below white children born to parents with comparable incomes. Racial disparities persist even at the highest income levels: among children whose parents are in the top 1% (who have incomes of \$1.1 million on average), the black-white gap remains at 12.4 percentiles. Hence, high levels of parental income provide no insulation against racial disparities.

The differences in mean ranks between black and white children arise from the fact that blacks both have much lower rates of upward mobility than whites and much higher levels of downward mobility (Bhattacharya and Mazumder 2011). For example, among children with parents in the bottom quintile, 10.6% of white children rise up to the top quintile, but only 2.5% of black children do (Table I). Among children with parents in the top quintile, 41.1% of white children remain in the top quintile, compared with 18.0% of black children. Perhaps most strikingly, black children starting from families in the top quintile have nearly the same chances of falling to the bottom income quintile (16.7%) as they do of staying in the top quintile.¹⁸

The estimates of intergenerational mobility shed light on how the black-white disparity will evolve across generations. Plugging our estimates of α_w and β_w into (3), the predicted steady-state mean rank for whites under the model in Section II is $\bar{y}_w^{SS} = 54.4$, illustrated by the point where the intergenerational mobility line intersects the 45 degree line on Figure IIa. The steady-state mean rank for blacks is $\bar{y}_b^{SS} = 35.2$. Hence, the predicted black-white gap in steady state given current levels of intergenerational mobility is $\Delta\bar{y}^{SS} = 19.2$ percentiles. Differences between blacks' and whites' incomes persist in steady state because black children continue to fall behind their white peers even if their parents catch up, as shown in Figure IIa.

Figure IIb plots the mean ranks of parents (circles) and children (diamonds) in our sample vs. the predicted steady-state mean ranks, by race. Both blacks and whites' mean incomes are close to their steady-state values, shown by the arrows intersecting the 45 degree line. The mean rank of black children in the 1978-83 birth cohorts is 34.8, while the mean rank of white children is 55.7.

¹⁸This result is not driven by measurement error in parental income: we average parent income over five years in our baseline analysis and find that using longer averages does not affect the results significantly.

Hence, the observed black-white gap in the current generation is 20.9 percentiles, which is very similar to the steady-state gap of 19.2 percentiles. Interpreted using the model in Section II, this result implies that blacks and whites are now in a steady-state where the black-white income gap is due almost entirely to differences in rates of intergenerational mobility rather than transitory or historical factors, consistent with the conclusions of Mazumder (2014). Thus, reducing the black-white gap in the long run requires reducing the black-white gap in children’s outcomes *conditional* on parental income ($\Delta\alpha$). However, interventions that reduce $\Delta\alpha$ could potentially lead to rapid convergence of incomes across generations because blacks have fairly high rates of relative mobility. For example, under the assumptions of the model in Section II, if black children’s mean ranks were increased by 13 percentiles at all levels of parental income, the black-white gap would fall to approximately 2.7 percentiles in two generations.

American Indians, Hispanics, and Asians. Figure IIIa shows intergenerational mobility series for Hispanics, Asians, and American Indians in addition to the series for whites and blacks plotted in Figure IIa. Rates of intergenerational mobility for American Indians are very similar to those for blacks. As a result, the predicted steady-state mean rank for American Indians is 36.5, similar to that for blacks. The mean rank of American Indian children is 36.7, showing that they too are very close to their steady-state (Figure IIb). Hence, American Indians’ low income levels are also due primarily to their low rates of upward mobility across generations.

Hispanics have rates of intergenerational mobility (among authorized immigrants and citizens) that are similar to those of whites, especially at the bottom of the income distribution. As a result, their predicted steady-state mean income is 48.7, only 5.7 percentiles below the steady-state for whites. But Hispanics’ current income distributions are closer to those of blacks and American Indians than whites (Online Appendix Figure II). Hispanic parents and children in our sample have a mean rank of 36.2 and 45.7 percentiles, respectively. Hence, unlike blacks and American Indians, Hispanics are on an upward trajectory across generations and may close most of the gap between their incomes and those of whites, as shown in Figure IIb. Their low levels of income at present thus appear to be primarily due to transitory factors.

Asians have much higher rates of relative mobility than all other groups, with $\beta = 0.18$. Asian children have high levels of income across the parental income distribution; even Asian children born to the lowest-income parents reach the 51st percentile of the national income distribution on average. These patterns have led to a perception that Asians are a “model minority” whose success may serve as a model for other racial groups. One concern with this inference is that 81.8% of Asian

parents in our sample are first-generation immigrants, who might have high levels of latent skill but low levels of observed income in the U.S., leading to unusually high rates of observed upward mobility for their children. We evaluate this hypothesis in Figure IIIb by focusing on children whose mothers were born in the U.S. (using data on year of entry to the U.S. for the subsample of mothers who appear in the 2000 Census long form or the ACS). Asian children whose mothers were born in the U.S. have outcomes very similar to white children. Hence, the exceptional outcomes of Asian children are unique to the children of first-generation immigrants rather than a persistent feature of Asians who are U.S. natives.¹⁹ Hence, Asian children of U.S. natives have a similar income trajectory to whites across generations, as shown in Figure IIb. Whether the same will be true of current Asian immigrants depends upon whether their own rates of mobility will remain high in future generations or will approach those of Asian children of U.S. natives.

In sum, Hispanics are moving up significantly in the income distribution across generations, whereas blacks and American Indians are stuck in a steady-state with lower levels of income. Understanding persistent disparities for these groups requires an understanding of the sources of intergenerational gaps: why do black and American Indian children have lower incomes than white children *conditional* on parent income? In the rest of the paper, we test a range of potential explanations for intergenerational gaps among black children. We focus specifically on the black-white gap because many of our tests require examining small subgroups, and sample sizes for blacks are much larger than those for American Indians.²⁰

V Marriage Rates and Gender Heterogeneity

We begin our analysis of the sources of black-white intergenerational gaps by considering a simple mechanical explanation: racial differences in marriage rates. It is well known that blacks marry at much lower rates than whites (e.g. Raley et al. 2015). Differences in marriage rates could potentially explain the intergenerational black-white gap in household income simply because we count two incomes for most white children but only one for most black children. In this section, we study the effects of differences in marriage rates by focusing on measures of individuals' own outcomes and show that the results vary sharply by gender.

We first document the large intergenerational gaps in marriage rates between black and white

¹⁹By contrast, Hispanic children whose mothers are born in the U.S. have only slightly lower earnings than (authorized) Hispanic immigrants; as a result, the predicted steady-state for Hispanic natives is 47.3 percentiles, only 1.4 percentiles below the value for all Hispanics.

²⁰For completeness, we present parallel analyses for other racial groups in the Online Appendix.

children in our sample. Figure IVa plots marriage rates for black and white children in 2015 (between ages 32-37) by parental income percentile. Black children have substantially lower marriage rates across the parental income distribution, with a gap of 32 percentage points (pp) for children with parents at the 25th percentile and 34 pp at the 75th percentile. White children at the bottom of the income distribution are as likely to be married as black children at the 97th percentile of the parental income distribution.

To evaluate the impacts of these differences in marriage rates, we focus on children’s *individual* incomes (excluding spousal income). Figure IVb plots children’s mean individual income ranks vs. their parents’ household income ranks, by race. The gap in individual income ranks is approximately 5 percentiles across the parental income distribution, substantially smaller than the approximately 13 percentile gap in household income in Figure IIa. Hence, differences in marriage rates do play an important role in driving the gaps in household income documented above.

However, the smaller gap in children’s individual incomes in Figure IVb masks substantial heterogeneity by gender. Figure V replicates Figure IVb separately for male and female children. This figure reveals that the black-white intergenerational gap in individual incomes is driven almost entirely by men. We find gaps for men of about 11 percentiles across the parental income distribution. In contrast, black women have 1 percentile *higher* individual income ranks than white women conditional on parental income.

Income Effects: Wage Rates and Hours of Work. One interpretation of the results in Figure V is that black-white gaps in labor market outcomes are small for women, but large for men. A competing explanation is that black women also have poorer labor market opportunities than white women, but this is masked by an income effect on labor supply: black women may be working harder to make up for having lower spousal income.

One way to distinguish these explanations is to compare the hours of work and wage rates of black and white women. In the simplest version of the income effect hypothesis, one would expect that black women would have higher hours than white women but lower wage rates. We measure annual hours of work and wages for children who appear in an ACS sample at or after age 30. We define wage rates as self-reported annual earnings divided by annual hours. We then convert hourly wages to percentile ranks by ranking individuals relative to others in the same birth cohort who received the ACS survey in the same year. Hours of work are coded as zero for those who do not work, while wages are coded as missing.

Figure VI plots mean wage ranks, hours, and employment rates by parental income percentile

for women and men. Conditional on parental income, black and white women have very similar wage rates, hours of work, and employment rates.²¹ These results suggest that the lack of an intergenerational gap in income for females is not due to an income effect. In contrast, there are very large gaps in both wage rates and hours of work for men. Conditional on parental income, black men have wages that are about 7 percentiles lower than white males, and work roughly 9 fewer hours per week on average. The gaps in employment rates for men are particularly stark, especially for children growing up in low-income families. Black men with parents at the 25th percentile are 18.9 pp less likely to work in a given year than white men, while black men with parents at the 75th percentile are 11.4 pp less likely to work than white men. The employment rates of black men with parents at the 75th percentile are comparable to those of white men with parents at the 9th percentile.

A limitation of the preceding analysis is that we observe wage rates only for those who are working. The black-white gap in wage rates may understate the true gap in potential wages if black women with lower wage opportunities are less likely to be employed (Heckman et al. 2000). The similarity of employment rates for black and white women rules out the simplest forms of selection bias in which the decision to work is based purely on potential wage rates. However, as noted by Neal (2004), it remains possible that the black women who do not work have low potential wage rates while the white women who do not work have high potential wage rates but a high marginal cost of labor. Although there is certainly scope for selection bias of this form, differences in potential wages for non-working women are unlikely to overturn the conclusion that the intergenerational gap in labor market opportunities is significantly smaller for women than men, for two reasons.

First, even among women born to high-income parents – for whom employment rates are around 90% – wages are very similar for blacks and whites. Second, we continue to find smaller intergenerational gaps for women and large intergenerational gaps for men for outcomes that are observed for everyone, such as educational attainment. Among children with parents at the 25th percentile, the black-white gap in high school completion rates is 3.5 pp for women vs. 8.3 pp for men (Figure VIIa-b). The corresponding gaps in college attendance rates are 2.8 pp for women and 6.5 pp for men (Figure VIIc-d). It is particularly noteworthy that high school completion and college atten-

²¹This is true not just for means: the entire distribution of black women's wage rates and hours of work is very similar to the corresponding distributions for whites, conditional on parent income (not reported). We also find that the occupational distributions of black and white women are similar conditional on parental income (Online Appendix Figure III), suggesting that black women are not substituting toward jobs with lower amenities to obtain higher wages.

dance rates are uniformly higher for black women than for white *men* across the parental income distribution.

The gender difference in racial disparities is perhaps most stark in incarceration. Figure VIIe shows that 21% of black males born to parents in the lowest-income (bottom 1%) families were incarcerated on April 1, 2010 (when they are between ages 27-32). In contrast, 6.4% of white males born to parents with comparable income were incarcerated. As parental income rises, the incarceration rates decline for both white and black males. But there are substantial disparities even at the top of the parental income distribution. Among children with parents in the top 1%, only 0.2% of white males were incarcerated, whereas 2.2% of black males were incarcerated – the same rate as for white boys who grew up in families at the 34th percentile of the parental income distribution. In contrast, incarceration rates are very low for both black and white females across the parental income distribution (Figure VIIf). These findings reinforce the view that the processes that generate racial disparities differ substantially by gender.²²

Implications for the Evolution of Income Disparities. We conclude based on the preceding analysis that the black-white intergenerational gap in individual income is substantial for men, but quite small for women. It is important to note, however, that this finding does not imply that the black-white gap in women’s individual incomes will vanish with time. This is because black women continue to have substantially lower levels of *household* income than white women, both because they are less likely to be married and because black men earn less than white men (Online Appendix Figure IV). As a result, black girls grow up in lower-income households than white girls in each generation, creating a persistent racial disparity in individual income for women even in the absence of an intergenerational gap in their individual incomes.

Nevertheless, the key to closing income disparities for both black and white women is to close intergenerational gaps in income between black and white men. We establish this result formally in Online Appendix D by extending the model in Section II to allow men’s and women’s individual income ranks to depend upon the individual income ranks of both men and women in the previous generation. The model predicts that in the absence of intergenerational gaps for women, the

²²Although there are large differences in incarceration rates between black and white men, incarceration itself cannot fully explain the black-white gaps in income for men documented in Figure Va. One way to see this is that the income gap remains substantial even among children in the highest-income families, for whom incarceration rates are much lower in absolute terms. Incarceration also cannot explain the sharp disparities observed in outcomes at younger ages, such as high school dropout rates. Moreover, incarcerated individuals have low levels of earnings even prior to incarceration (Looney and Turner 2017). We therefore treat incarceration as an endogenous outcome determined by some of the same processes that shape education and labor market outcomes. We defer consideration of factors that may directly increase incarceration rates for black men and depress their subsequent earnings, such as discrimination in the criminal justice system (Steffensmeier et al. 1998; Pager 2003), to future work.

steady-state gap for both women and men is proportional to the intergenerational gap in individual incomes for men.²³ We therefore focus on understanding the determinants of intergenerational gaps between black and white men in the rest of the paper.

VI Family-Level Factors

In this section, we ask whether other factors that vary across black and white families beyond parental income can explain intergenerational gaps in income between black and white men. We consider four family-level factors that have received attention in the previous literature, summarized in Online Appendix Table I: parental marital status, parental education, parental wealth, and differences in ability.

We study the role of parental characteristics by estimating regressions on the subsample of black and white children of the form:

$$y_{i,c} = a + b_p y_{i,p} + b_w \text{white}_i + b_{wp} \text{white}_i \cdot y_{i,p} + \gamma X_i + \varepsilon_i, \quad (5)$$

where $y_{i,c}$ is the child’s individual income rank, $y_{i,p}$ is the parent’s household income rank, white_i is an indicator for the child being white, and X_i is a covariate such as parental education. In this specification, the intergenerational gap in income between blacks and whites at a given parental income rank \bar{p} , controlling for the effect of X_i , is $\Delta_{\bar{p}|X} = b_w + b_{wp}\bar{p}$. Our goal is to assess how $\Delta_{\bar{p}|X}$ changes as we control for various factors X .

In Figure VIII, we show how $\Delta_{\bar{p}|X}$ changes as we control for various factors X . Panel A considers the black-white gap for children growing up in low-income ($\bar{p} = 25$) families, while Panel B considers the gap for those growing up in high-income ($\bar{p} = 75$) families. As a reference, the first two bars in both panels report the unconditional difference in white and black children’s mean individual income ranks, without controlling for parental income or any other covariate. This unconditional gap is 17.6 percentiles for males and 4.8 percentiles for females. The second set of bars report estimates of $\Delta_{\bar{p}}$ when no controls X_i are included. These estimates correspond to the difference between the black and white series in Figure IVb at the 25th and 75th percentiles (under a linear approximation for both series). For men, the baseline intergenerational gap in individual income is

²³In our model, we abstract from marital choices. In practice, closing intergenerational gaps in income for fathers may require both closing the gap in men’s incomes and closing the gap in marital rates, if father’s incomes matter more if they are part of the household raising the child. We cannot investigate this issue directly in our data because we cannot link children to their fathers if the father is not present in their household (i.e., does not claim them as a dependent). We therefore focus on understanding intergenerational gaps in income and defer investigation of intergenerational gaps in marital patterns to future work.

10.0 percentiles at $\bar{p} = 25$ and 11.7 percentiles at $\bar{p} = 75$. For women, the corresponding gaps are -2.0 at $\bar{p} = 25$ and -0.9 at $\bar{p} = 75$.

The rest of the bars in Figures VIIIa-b show how these intergenerational gaps change with the introduction of additional controls, X_i . One prominent hypothesis is that black children have poorer outcomes because they are more likely to grow up in single parent families, and boys who grow up in single-parent families tend to have worse outcomes (Autor et al. 2016; Lundberg 2017). The third set of bars in Figure VIIIa-b show that controlling for parental marital status in (5) has a small effect on the intergenerational gap. At the 25th percentile, the intergenerational income gap for men falls from 10 to 9.3 percentiles; at the 75th percentile, it falls 11.7 to 11.4 percentiles.²⁴

One may be concerned that the model in (5) assumes that parental marital status has an additive effect on children’s outcomes – i.e., that it does not have differential effects across the parental income distribution. In Online Appendix Figures Va-b, we relax this parametric assumption by conditioning on parental marital status and replicating Figure Va separately for boys in single- and two-parent families. The black-white intergenerational gaps remain similar to the estimates obtained from (5) in both of these groups, confirming that parental marital status has little impact on intergenerational gaps.²⁵

Next, we assess the role of differences in parental education by including indicators for parents’ highest level of educational attainment in (5) (see Section III for details on how educational attainment is defined). Controlling for parental education in addition to marital status reduces the gap for men to 9.1 percentiles at $\bar{p} = 25$; at $\bar{p} = 75$, the gap remains unchanged at 11.4 percentiles. Hence, including parental education controls does not significantly affect the black-white intergenerational gap $\Delta_{\bar{p}}$.

Finally, we assess the role of differences in parental wealth. Black families have much lower

²⁴Since these estimates are based on OLS regressions in observational data, they may not capture the causal effect of parental marital status on children’s outcomes. However, under the plausible assumption that having married parents is positively correlated with other unobservables (ε_i) that also improve children’s outcomes (e.g., parental wealth), our estimates of the changes in the intergenerational gap provide an upper bound on the true impact of parental marital status on $\Delta_{\bar{p}}$. Intuitively, the OLS regression overestimates the true impact of having married parents (γ) when $Cov(X_i, \varepsilon_i) \geq 0$ and therefore understates the black-white gap that would remain after controlling for the causal effect of differences in parental marital status between blacks and whites. Following analogous reasoning, the analysis of the other family characteristics below also likely provides an upper bound on their causal impacts on intergenerational gaps.

²⁵This result shows that parental marital status has little impact on the black-white gap *conditional* on parental income. When we do not control for parent income, controlling for marital status has a larger effect, reducing the unconditional black-white gap from 17.6 to 13.3 percentiles (Online Appendix Figure VI). This is intuitive, as having two parents in the household is associated with a higher level of household income. The impact of parental marital status on the unconditional black-white gap is consistent with the findings of Autor et al. (2016). We focus here on how controls affect the intergenerational gap (i.e., the gap conditional on parental income) because that is the parameter relevant for the dynamics of racial disparities across generations, as shown in Section II.

levels of wealth than white families, even conditional on income (Oliver and Shapiro 2006), and these wealth differences could impact children’s opportunities. We control for several proxies for wealth reported in the ACS: home ownership, monthly mortgage payments, home value, and the number of vehicles (see Section III for details on definitions). Including these variables as controls reduces the black-white income gap modestly for males, to 8.4 percentiles at $\bar{p} = 25$ and 11.0 percentiles at $\bar{p} = 75$. Controlling non-parametrically for wealth, e.g. by conditioning on the subset of families who do not own houses, yields similar results (Online Appendix Figure Vc).

In sum, controlling for parental marital status, education, and wealth reduces the black-white intergenerational gap for men by 16% of the initial 10 percentile gap for men growing up in families at the 25th percentile and 6% for men growing up in families at the 75th percentile. As noted above, these estimates likely overstate the true impacts of these family-level factors because of omitted variable biases. We therefore conclude that differences in these parental characteristics play a small role in explaining why black men have lower levels of absolute mobility than white men.²⁶

Ability. The last family-level explanation we evaluate is the hypothesis that there are genetic differences in cognitive ability by race. Since we do not have measures of innate ability in our data, we cannot use the same approach as above to evaluate this explanation. However, there are two pieces of evidence which suggest that differences in ability are unlikely to explain the intergenerational gaps we document. First, the prior literature suggests no ex-ante biological reason that racial differences in cognitive ability would vary by gender (Rushton and Jensen 2005). Hence, our finding that intergenerational black-white gaps vary so sharply by gender casts doubt on ability as an explanation for the gaps we observe for men.

Second, most prior arguments for the ability hypothesis rest upon the large gaps observed between black and white children on standardized tests (e.g., Herrnstein and Murray 1994). However, black-white test score gaps do not vary significantly by gender. Data from the National Assessment of Educational Progress show that the black-white gap in test scores at age 9 for low-income (free- or reduced-price lunch-eligible) children is 0.48 standard deviations (SD) for boys vs. 0.44 SD for girls (Online Appendix Figure VIII). The fact that black women have incomes and wage rates comparable to white women conditional on parental income despite having much lower test scores suggests that test scores do not provide an accurate measure of differences in ability (insofar as it is relevant for earnings) by race. Instead, these results buttress prior work showing that blacks

²⁶We present analogous results for Hispanics, Asians, and American Indians in Online Appendix Figure VII. As with the black-white gap, we find that controlling for other family-level factors has little impact on intergenerational gaps between these other racial groups and whites.

under-perform on standardized tests relative to whites because of factors such as stereotype threat and inherent biases in tests (Steele and Aronson 1995; Jencks and Phillips 1998).

In summary, our results suggest that black-white intergenerational gaps in boys' outcomes are not explained by the family-level factors most commonly discussed in prior work.

VII Neighborhood-Level Factors

In this section, we use variation across neighborhoods as a lens to study how environmental factors affect intergenerational mobility for black and white men. Since neighborhoods vary on many dimensions that can affect individuals' outcomes – from the quality of local schools to the availability of jobs to the degree of racial bias – studying differences in outcomes across neighborhoods is a fruitful way to learn about the effects of environmental factors (e.g., Wilson 1987; Cutler and Glaeser 1997; Sampson et al. 2002b; Sharkey and Faber 2014).

We organize our analysis into four sections. First, we characterize broad regional variation in black-white gaps across commuting zones (CZs), which are aggregations of counties that are commonly used as a definition of local labor markets. Since blacks and whites often live in different parts of a given CZ, we next examine variation in outcomes by race at much finer geographies, by Census tract and block. Having characterized the observational variation in outcomes across neighborhoods, in the third subsection, we study the outcomes of children whose families move across areas to determine whether the neighborhood-level differences in black-white gaps that we document are driven by causal effects of environment or sorting. Finally, we compare the types of neighborhoods in which black and white children grow up to evaluate the extent to which changes in neighborhood environments could close the black-white gap.

Throughout this section, we focus on characterizing how the neighborhoods in which children *grow up* affect their outcomes, which may differ from the neighborhoods in which they live as adults. We focus on childhood neighborhoods because of prior evidence that rates of intergenerational mobility depend on where children grow up rather than where they live as adults (Chetty et al. 2016; Chetty and Hendren 2018a).

VII.A Variation Across Commuting Zones

We first characterize black-white intergenerational gaps across CZs. Chetty et al. (2014) and Chetty and Hendren (2018a) demonstrate that there is substantial variation in intergenerational mobility across CZs in the full population, pooling all racial groups. Here, we disaggregate their analysis

by race to determine the extent to which certain regions of the country produce particularly good outcomes for blacks or whites.

We assign children to CZs based on where they grow up. Chetty and Hendren (2018a) show that the CZ in which one grows up has causal effects on earnings and other outcomes in adulthood until approximately age 23. We therefore assign children to CZs in proportion to the amount of time they spend below age 23 in each commuting zone over the years observed in our sample.²⁷ For instance, if a child spent half of his childhood in the New York City CZ and half of his childhood in the Boston CZ, he would receive a weight of 0.5 in each of these CZs.

We characterize the mean income ranks of children of race r who grow up in CZ c conditional on their parents' ranks using the linear specification in (1).²⁸ We regress children's individual income ranks in the national income distribution on their parent's household income ranks in the national income distribution:

$$y_{i,c} = \alpha_r^c + \beta_r^c y_{i,p} + \epsilon_i, \quad (6)$$

weighting by the number of years that child i is observed below age 23 in CZ c . This regression yields estimates of absolute mobility for children with parents at $p = 0$ (α_r^c) and relative mobility β_r^c , for each CZ, c . We combine these estimates to report levels of absolute mobility at two parent income levels: $p = 25$ (corresponding to the outcomes of children of below-median-income parents) and $p = 75$ (above-median-income parents). We focus primarily on the estimates at $p = 25$ in the main text because most black children presently grow up in relatively low-income families, but we show that results are analogous at $p = 75$ in the Online Appendix.

Figure IX maps the mean individual rank of male children with parents at the 25th percentile of the national household income distribution, $\bar{y}_{25}^{cr} = \alpha_r^c + .25\beta_r^c$, for white and black men.²⁹ The maps for both races are colored on a single scale: dark green colors represent areas with the highest levels of upward mobility (i.e., higher \bar{y}_{25}^{cr}), yellow denotes colors with average levels of upward mobility, and dark red represent areas with the lowest levels of upward mobility.

The maps reveal three lessons. First, looking within each panel, there is substantial variation in children's rates of upward mobility across areas, for both blacks and whites. For example, the

²⁷Since the tax records begin in 1989, the earliest age at which we observe children's locations in our data is age 6 (for the 1983 birth cohort).

²⁸Chetty et al. (2014) show that the relationship between children's mean ranks and their parents' ranks is approximately linear in all CZs, and we have verified that this continues to be the case when further disaggregating the data by race.

²⁹In Online Appendix Figures IX-XII, we present analogous maps for females, children growing up in high-income families ($p = 75$), children of Hispanic origin, and using household income ranks instead of individual income ranks. The CZ-level estimates of $\{\bar{y}_p^{cr}\}_{r,c,p}$ plotted in all of these maps are available in the Online Data Tables.

difference between the 90th and 10th percentile outcomes for both white and black men is roughly 10 percentiles, which is the same as the average black-white income gap in the U.S. as a whole.

Second, the areas in which white children have better outcomes tend to be places where black children have better outcomes as well, although the patterns are not identical. The correlation between \bar{y}_{25}^{cr} for blacks and whites, weighting by total CZ population, is 0.5. The geographic patterns, especially for whites, largely mirror those documented in Chetty et al. (2014), which pool across races. For both blacks and whites, rates of upward mobility are highest for children who grow up in the Great Plains and the coasts and lowest in parts of the industrial Midwest. For example, Boston has outcomes towards the top of the within-race distribution for both white and black men, whereas Knoxville, TN has outcomes at the bottom of the distribution for both groups. One notable exception to this pattern is the Southeast, where whites have especially low rates of upward mobility relative to other areas but blacks do not. Among white men with parents at the 25th percentile of the national income distribution, those who grew up in Atlanta have a mean rank of 46.6, significantly lower than those who grew up in Chicago, who have a mean rank of 52.6. In contrast, black men who grew up in Atlanta have a mean rank of 37.7, *higher* than the mean rank of 36.8 of low-income black men who grew up in Chicago.

Third, there are substantial differences in black and white boys' outcomes *within* virtually all CZs, for both children with parents at the 25th and 75th percentiles. Indeed, we find that the distributions of outcomes for blacks and whites across CZs are almost non-overlapping, consistent with the broad regional patterns documented in contemporaneous work by Mazumder and Davis (2018) using survey data. At the 90th percentile of the (unweighted) CZ-level distribution, black boys have a mean income rank of 45.1, which falls at the 16th percentile of the corresponding distribution for white boys.

In sum, Figure IX shows that children's rates of upward mobility vary substantially across areas – suggesting that environmental factors may play an important role in children's outcomes – yet black children do not have the same prospects for upward mobility as white children in the vast majority of areas.

VII.B Variation Across Census Tracts

Although the CZ-level analysis is useful in illuminating broad regional patterns, it does not directly test whether differences in neighborhood quality explain black-white gaps because black and white children grow up in very different neighborhoods within metro areas (Reardon et al. 2008). We

therefore focus most of our neighborhood-level analysis on finer geographies, in particular analyzing variation across Census tracts. There are approximately 70,000 Census tracts in the United States, which contain 4,256 people on average.

We estimate intergenerational mobility at the tract level by estimating the regression specification in (6) for each Census tract separately by race and gender. This subsection summarizes the key properties of these tract-level estimates of intergenerational mobility, $\bar{y}_{25}^{cr} = \alpha_r^c + .25\beta_r^c$, for white and black men.

Black-White Gaps Persist Within Tracts. One of the most well-known explanations for the black-white gap is residential segregation: blacks and whites may have different outcomes because they tend to live in different neighborhoods (e.g., Massey and Denton 1993). To test this hypothesis, we include Census tract fixed effects in equation (5), effectively comparing the outcomes of children raised in the same neighborhood.³⁰ Figure Xa shows that including tract fixed effects reduces the intergenerational black-white gap among boys with parents at the 25th percentile ($p = 25$) from 10.0 percentiles to 7.7 percentiles. Indeed, even when we compare children who grow up on the same Census blocks (which contain 50 people on average) by adding block fixed effects, the intergenerational gap for boys remains at 7 percentiles at $p = 25$ and 7.9 percentiles at $p = 75$. In short, the vast majority of the black-white gap persists even among boys growing up in families with comparable incomes in the same neighborhood; differences in neighborhood quality explain at most 25% of the black-white gap.³¹

Figure Xb illustrates why this is the case by presenting a histogram of the intergenerational black-white gap in each tract for boys with parents at the 25th percentile of the income distribution, $\Delta\bar{y}_{25}^{bw} = \bar{y}_{25}^{cw} - \bar{y}_{25}^{cb}$, weighting by the number of black men who grew up in each tract. Consistent with Figure Xa, the mean gap within tracts is 7.5 percentiles. The raw standard deviation of $\Delta\bar{y}_{25}^{bw}$ is 6.6 percentiles. However, some of this variance is due to sampling variation resulting from small samples at the tract level. Subtracting the variance due to sampling error from the total variance yields an estimated signal standard deviation of the latent black-white gaps within tracts of 3.4

³⁰We use the first observed Census tract for individuals who move across tracts in childhood. Replicating the analysis on children who remain in the same tract for several years or their entire childhood yields very similar results.

³¹The small reduction in the intergenerational gap does not mean that neighborhoods do not matter for children's outcomes. Since neighborhood choice itself is an endogenous variable, one cannot separate the contribution of neighborhoods from parental income directly in observational data. Indeed, including Census block fixed effects without controlling for parent income reduces the unconditional black-white gap for males from 17.6 to 9.8 percentiles, similar to the effect of controlling for parental income. Intuitively, parent income itself might matter because it allows parents to buy access to better neighborhoods for their children. As discussed above, we focus on how the gap conditional on parental income changes when we control for neighborhood fixed effects because that is what matters for the evolution of racial disparities in the long run.

percentiles.³² This noise-corrected standard deviation implies that among children with parents at the 25th percentile ($p = 25$), white boys have higher incomes in adulthood than black boys in 98.7% of tracts.³³

The results in Figure X imply that reducing *residential* segregation alone may be insufficient to close the black-white gap, since substantial disparities persist within neighborhoods. Moreover, since low-income children who live on the same block are likely to attend the same schools, simply enabling black and white children to attend the same schools, without creating greater racial integration within schools or making other changes that have differential effects by race, is also likely to be insufficient to close the gap.

Although black-white gaps exist in virtually every neighborhood in the U.S., there is nevertheless substantial variation in the *magnitude* of these gaps across areas, as shown in Figure Xb. In the rest of this subsection, we use this variation across tracts to understand the characteristics of places where black boys have better outcomes and where there are smaller intergenerational gaps.

Black-White Gaps Are Larger in “Good” Neighborhoods. We begin by analyzing the most commonly used measures of neighborhood quality in prior work on neighborhoods (e.g., Sampson et al. 2002a). We obtain data on a variety of proxies for neighborhood quality – such as poverty rates, test scores, educational attainment of local residents, housing costs, and family structure – at the tract level from the publicly available 2000 Census long form and other sources. Details on sources and definitions of these variables are given in Online Appendix C.

Figure XIa plots the correlation between a selected subset of tract-level characteristics and the mean individual income ranks of black boys (solid circles) and white boys (open circles) with parents at the 25th percentile (\bar{y}_{25}^{cf}). All of these tract-level characteristics are defined so that the correlation between the characteristic and the outcome for white males is positive (e.g., we use the share above the poverty line rather than the poverty rate).

We find positive correlations between each of these proxies for neighborhood quality and the outcomes for both white and black men. For example, black and white boys who grow up in neighborhoods with lower poverty rates, higher test scores, higher median rents, and more two-parent households tend to have higher incomes in adulthood. These findings reinforce prior work showing that children who grow up in higher-income areas with more stable family structure and

³²We estimate the variance due to sampling error as the mean of the square of the standard errors of the estimated gaps, which are obtained from the regression in (5).

³³At $p = 75$, white boys have higher incomes in adulthood than black boys in 98.1% of tracts (Online Appendix Figure XIII). In contrast, black girls have higher incomes than white girls in 84% of tracts conditional on having parents at $p = 25$ and 69% of tracts at $p = 75$ (Online Appendix Figure XIV).

higher test scores typically have better outcomes (e.g., Chetty et al. 2016; Chetty and Hendren 2018b).³⁴

The correlations in Figure XI are generally larger for whites than for blacks. As a result, “good” neighborhoods tend to have *larger* intergenerational gaps between blacks and whites. Figure XIb illustrates this point by presenting a binned scatter plot of the relationship between the black-white intergenerational gap for boys ($\Delta \bar{y}_{25}^{bw} = \bar{y}_{25}^{cw} - \bar{y}_{25}^{cb}$) and the fraction of residents in the tract who are above the poverty line. This plot is constructed by dividing the fraction above the poverty line into 20 equal-sized bins (weighting by the number of black men) and plotting the means of the x and y variables within those bins. The mean intergenerational gap increases by 2.5 percentiles when moving from the highest poverty neighborhoods to the lowest poverty neighborhoods. Intuitively, both black and white boys have higher incomes in low-poverty areas, but the effect of growing up in a low-poverty area is larger for whites than blacks. As a result, black-white gaps are larger in low-poverty neighborhoods than in high-poverty neighborhoods.

Characteristics of Neighborhoods with Smaller Intergenerational Gaps. In light of these findings, we next investigate whether there are certain neighborhoods where black boys both do well *and* black-white gaps are smaller. As a first step in identifying such areas, we establish that the neighborhoods in which low-income black boys have high incomes – which we define as reaching above the national median on average – are almost exclusively low-poverty neighborhoods. Figure XII illustrates this result by presenting a binned scatter plot of the fraction of tracts in which $\bar{y}_{25}^{cb} > 50$ vs. the share of residents above the poverty line. The subset of neighborhoods in which the average rank of low-income black boys is above the 50th percentile almost all have poverty rates below 10% (demarcated by the dashed line on the figure), which is approximately the median (population-weighted) poverty rate across tracts in the U.S. We therefore zoom in on areas with a poverty rate below 10% to identify places where low-income black boys do well in both absolute levels and relative to their white peers.

In Figure XIII, we correlate various tract-level characteristics with the black-white gap at $p = 25$ ($\Delta \bar{y}_{25}^{bw}$) to identify the characteristics of areas with smaller intergenerational gaps. In addition to the more traditional proxies for neighborhood quality considered above, we expand the set of tract-level characteristics we consider to include a set of race-specific measures – such as poverty rates for black and white families – as well as other variables that have differential effects by race, such as measures of racial bias. To isolate variables that are uniformly associated with better outcomes for

³⁴Of course, these correlations do not imply that these factors have causal effects on children’s outcomes.

black boys, we focus on the subset of characteristics whose correlations with black boys' outcomes have the same sign at *both* the 25th and 75th percentile of the parental income distribution. We then redefine all variables so that they are positively correlated with \bar{y}_{25}^{cb} by multiplying those that have negative correlations with \bar{y}_{25}^{cb} by -1 .³⁵

Mirroring the pattern documented above, most of the tract-level characteristics we examine are associated with larger black-white gaps. That is, neighborhood characteristics associated with better outcomes for black boys are associated with larger intergenerational gaps relative to whites. However, there are a small number of variables that are associated with smaller gaps. The strongest of these are measures of father presence and marriage rates, which we now investigate in further detail.

Father Presence. Among all the characteristics in Figure XIII, the fraction of low-income black fathers present is most predictive of smaller intergenerational gaps. We define father presence as an indicator for whether the child is claimed by a male on a tax form in the year he is matched to a parent. We regress this indicator for father presence on parental income rank for each tract using equation (6), and define black father presence among low-income families as the prediction for black children at $p = 25$.

Figure XIV characterizes the association between father presence and children's outcomes across tracts. In Panel A, we present a binned scatter plot of low-income black and white boys' mean income ranks in adulthood, \bar{y}_{25}^{cb} and \bar{y}_{25}^{cw} , vs. black father presence, among the subset of low-poverty tracts. Consistent with the correlation in Figure XIII, we find a strong positive association between black father presence and black males' incomes. In contrast, we find no association between black father presence and white males' outcomes. Because of this differential effect by race, the black-white intergenerational gap is 6.1 percentiles in tracts with the highest levels of black father presence, compared with 9.3 percentiles in the tracts with the lowest levels of father presence.

Panel B shows that these differences are even more stark when we focus on the extensive margin of employment: black boys' employment rates (measured as having positive income in the tax data in either 2014 or 2015) are significantly higher in tracts with higher levels of black father presence. Among low-poverty tracts with the highest levels of black father presence, the black-white gap in employment rates is 4 pp, as compared with 9 pp in the nation as a whole. Panel C shows that black boys who grow up in areas with high father presence are also significantly less likely to be

³⁵Online Appendix Table XI provides the full set of variables and reports their correlations with the mean income ranks of low-income white and black males in low-poverty neighborhoods. Online Appendix Tables X and XII report analogous correlations for the full sample of tracts and for females.

incarcerated, which could explain part of the association with higher employment rates. Panel D replicates Panel B, comparing the employment rates of black boys and girls. It shows that black father presence predicts boys' employment rates, but not girls employment rates.³⁶

Together, the results in Figure XIV show that black father presence is associated with children's outcomes in a highly race-by-gender specific manner. Although we cannot make strong causal claims based on this correlational evidence, the specificity of this set of correlations rules out broad mechanisms that would affect both genders and races (such as differences in the quality of schools). Instead, it points to channels that affect black boys in particular, such as mentoring by black male role models in the community or differences in the way black men are treated by their peers and adults in areas where black fathers are involved in their children's households.

We probe the robustness of these conclusions further in Table II. In Column 1, we regress the predicted income ranks of black males at $p = 25$ (\bar{y}_{25}^{cb}) on low-income black father presence, weighting by the number of black boys who grow up in each tract. Children who grow up in a tract with 10 pp more low-income black fathers present have incomes that are 0.5 percentiles higher on average, consistent with Figure XIVa. Column 2 shows that the pattern is driven by the presence of low-income black fathers, not white fathers; including both variables in the regression yields a coefficient of 0.045 (s.e. = 0.0068) on the presence of low-income black fathers and 0.0077 (s.e. = 0.0076) for white fathers. Column 3 shows that these patterns are not simply driven by regional differences, by showing that the results are very similar when we include state fixed effects.

The patterns documented thus far could potentially reflect the impact of a child's own parents marital status, as opposed to the fraction of fathers present in the neighborhood, since a child's own father is more likely to be present in neighborhoods with high levels of father presence. We evaluate this hypothesis by restricting the subsample of children to families with a father absent (Column 4) and two-parent families (Column 5). We continue to find a strong association of black boys' outcomes with neighborhood-level presence of black fathers in both of these subsamples. Hence, the association with father presence is driven by a characteristic of the neighborhood in which the child grows up, not simply a direct effect of the marital status of one's own parents, consistent with the findings of Sampson (1987).

Next, we investigate whether the association with father presence is driven by black fathers

³⁶Symmetrically, we find that the employment rates of low-income white men are predicted by the fraction of white fathers present and the employment rates of women are likewise predicted by the fraction of mothers present. But rates of father presence among whites and rates of mother presence (for both blacks and whites) are generally quite high, making this a less important factor in explaining the variance of outcomes for those subgroups than for black men.

in particular or the presence of black men in general. There are many “missing black men” in certain neighborhoods, due to high incarceration and mortality rates (Wolfers et al. 2015), raising the possibility that the correlations above are driven by the presences of males in a neighborhood in general, rather than by father presence in particular. To distinguish these explanations, we calculate two measures: the number of low-income males in each tract in 2000 in the Decennial Census and the number of below-median-income black fathers in the tract in 2000. We divide both of these counts by the number of black children in our analysis sample in each tract to obtain a measure of black male presence and a comparable measure of black father presence.

To maximize statistical precision, we compare the predictive power of these two variables in the full sample rather than the subset of low-poverty tracts. Column 6 shows that we continue to find a strong positive association between black father presence and black boys’ earnings outcomes in the full sample. Column 7 shows that this remains the case when we use the count-based measure of black father presence defined above from the 2000 Census, although the magnitude of the coefficient is lower, which is to be expected given that the sample from which the variable is constructed (in 2000) does not overlap with the set of children whose outcomes are being measured. Column 8, which is the key specification of interest, shows that when we include both black father presence and black male presence in the regression, black father presence remains just as predictive as in Column 7 whereas black male presence is not significantly related to black boys’ outcomes. Hence, what matters appears to be the number of black men involved in raising children in a tract, not the number of black men overall.

Finally, we test the hypothesis that black boys’ outcomes are associated with black father presence because they may both be affected by the same set of policies or shocks that persist over time in an area (such as high rates of arrests or incarceration). In Column 9, we include fixed effects for the tract in which the child lives as an adult (in 2015), thereby comparing children who grew up in different areas but currently live in the same place. We continue to find a strong positive relationship, with a slope similar to the corresponding estimate without tract fixed effects in Column 6. Hence, what matters is the fraction of low-income fathers present in the tract in which the child *grows up* even holding fixed where they live as adults, ruling out the possibility that the same exogenous factors that affect black father presence also affect black boys’ outcomes.

In sum, we find robust evidence that greater black father presence is associated with better outcomes for black-boys (but not white boys and black girls), irrespective of their own parents’ marital status. While we cannot be certain of the precise mechanism underlying this finding, one

pattern that is suggestive of the types of mechanisms that may be at play is that black children have significantly lower rates of suspension from school in areas with higher black father presence (Online Appendix Figure XV), suggesting that black boys may have fewer disciplinary infractions in such areas. However, white children are significantly less likely to be suspended in such areas (although with a smaller gradient) as well. This raises the possibility that what drives the race-specific patterns documented above for earnings and employment are not changes in behavior unique to black boys but rather racial differences in the treatment of a given set of disciplinary issues. Further analysis of these associations and the causal mechanisms underlying them would be a valuable direction for future work, especially given the specificity and uniqueness of the correlations between black-white gaps for boys and black father presence.

Racial Bias. We now turn to another set of factors that are associated with both better outcomes for black boys and a smaller black-white gap in low-poverty tracts: lower levels of racial bias among whites. Prior work has shown that exposure to racial bias during childhood adversely affects black youth, especially black boys, in school (e.g. Simpson and Erickson 1983, Chavous et al. 2008). Here, we investigate whether these effects are associated with adverse long-term outcomes.

We focus on two measures of racial bias. The first is a measure of implicit racial bias from implicit association tests (IAT), which measure the difference in a participant’s ability to match positive and negative words with black vs. white faces (Greenwald et al. 1998). We obtain mean IAT racial bias scores for white and black study participants (with higher values representing greater bias) at the county level from the Race Implicit Association Database. The second measure we use is the Racial Animus Index constructed by Stephens-Davidowitz (2014). This is a measure of explicit racial bias, based on the frequency of Google searches for racial epithets at the media market level, which are aggregations of counties. We standardize all the racial bias measures used below so that they have mean zero and standard deviation 1 across areas (weighting by the number of black males in our sample), with higher values representing greater racial bias against blacks.

We did not include these racial bias measures in Figure XIII because they are not available at the Census tract level. Nevertheless, among all the variables we consider (at both the tract level and broader geographies) that are not associated with larger black-white gaps, the racial bias measures have the strongest correlations with black boys’ income ranks at both $p = 25$ and $p = 75$ within low-poverty areas (Online Appendix Table XI).³⁷

³⁷We restrict the sample to counties with poverty rates below 10% for the IAT correlation and media markets with poverty rates below 10% for the racial animus correlation. We also consider a third measure of racial bias: attitudes regarding interracial marriage in the General Social Survey, as constructed by Mas and Moretti (2009). This measure

Table III characterizes the association between measures of racial bias and children’s outcomes using a series of regression specifications. We restrict the sample to counties or media markets with poverty rates below 10% and weight the regressions by the number of black men in the relevant geographic unit. We begin in Column 1 by regressing the mean individual income rank of black boys (\bar{y}_{25}^{cb}) in each county on the (standardized) difference between whites’ and blacks’ mean IAT scores. Counties with a 1 SD higher level of racial bias against blacks have mean income ranks that are 0.8 percentiles lower, implying that the difference in black boys’ incomes between the least (bottom 5%) and most (top 5%) racially biased areas exceeds 4 percentiles. In Column 2, we regress black boys’ mean income ranks on whites’ and blacks’ IAT scores separately. As one might expect intuitively, the negative correlation is driven entirely by bias among white respondents. Column 3 shows that results remain similar when we include state fixed effects, showing that the pattern is not driven purely by broad regional variation in levels of racial bias.

Columns 4 and 5 of Table III show that low-income black males are more likely to be employed and less likely to be incarcerated if they grow up in counties with less racial bias, although the relationship with incarceration rates is not statistically significant. Column 6 shows that, in contrast to the pattern for father presence, correlations with racial bias are not gender-specific: black females also have lower incomes in places that are more racially biased against blacks. Perhaps more surprisingly, Column 7 shows that low-income white males also have lower incomes if they grow up in areas with greater racial bias against blacks. One potential explanation for this association is that implicit racial bias is correlated with other forms of bias that adversely affect low-income white men.³⁸

The patterns are very similar when we use the Racial Animus Index to proxy for racial bias. Black boys who grow up in low-income ($p = 25$) families in media markets with greater racial animus have lower incomes in adulthood (Column 8), are less likely to be employed (Column 9), and are more likely to be incarcerated (Column 10). As with the IAT results, we find the results are not gender- or race-specific: low-income black women and white men who grow up in areas with more explicit racial animus have lower incomes (Columns 11 and 12).

To summarize, the correlational analysis in this section reveals that the neighborhoods that have higher rates of upward mobility for black boys and relatively small black-white gaps tend to

yields similar point estimates but much larger standard errors because it is only available at the state level.

³⁸An alternative explanation is that the degree of racial bias is endogenous: whites may be more biased in areas with lower earnings outcomes. A third possibility is that racial bias is correlated with other latent factors that drive these correlations.

have three characteristics: (1) low poverty rates, (2) a high fraction of low-income black fathers, and (3) low levels of racial bias among whites.

VII.C Causal Effects of Neighborhoods on Intergenerational Gaps

The neighborhood-level variation in black-white intergenerational gaps documented above could be driven by two very different sources. One possibility is that neighborhoods have causal effects on children’s outcomes: that is, moving a given child to a different neighborhood would change his outcomes. Another possibility is that the geographic variation is due to unobserved differences in the types of people living in each area. Building on the quasi-experimental research design of Chetty and Hendren (2018a), we assess the relative importance of these two explanations by studying how the outcomes of children who move across areas vary with the age at which they move. Chetty and Hendren (2018a) use this timing-of-move design to establish that neighborhoods have causal effects on children’s outcomes pooling all racial groups; here, we use the same design to identify the causal effects of areas on racial disparities by showing that neighborhoods have *race-specific* causal effects.

Empirical Specification. Following Chetty and Hendren (2018a), we study the outcomes of children who move across CZs exactly once during their childhood. We focus on CZ-level variation for this analysis because the larger sample sizes at the CZ level allow us to generate precise estimates of the outcomes of people who grow up in each area, which is essential for identifying race-specific causal effects.

Let i index children, p_i denote their parental income ranks, and r_i denote their racial groups. In the sample of one-time movers, let m_i denote the age at which child i moves from origin CZ o to destination CZ d . Let \bar{y}_{pls}^r denote the exposure-weighted outcome of $y_{i,c}$ for children of race r in birth cohort s who grew up in location l with parental household income rank p , estimated using the specification in (6).³⁹ Let $\Delta_{odps}^r = \bar{y}_{pds}^r - \bar{y}_{pos}^r$ denote the predicted difference in income ranks in the destination versus origin CZ for children in cohort s . After computing these variables, we regress the income rank of children who move ($y_{i,c}$) on the measures of origin and destination quality interacted with age-at-move fixed effects:

³⁹We do not include one-time movers when constructing these exposure-weighted outcomes to ensure that a child’s own outcome does not enter our definition of neighborhood quality; see Online Appendix E for details.

$$\begin{aligned}
y_{i,c} = & \sum_{s=1978}^{1986} I(s_i = s)(\phi_s^1 + \phi_s^2 \bar{y}_{pos}^r) + \sum_{m=2}^{28} I(m_i = m)(\zeta_m^1 + \zeta_m^2 y_{i,p}) \\
& + \sum_{m=2}^{28} b_m I(m_i = m) \Delta_{odps}^r + \varepsilon_i,
\end{aligned} \tag{7}$$

where ϕ_s^1 is a cohort-specific intercept, $\phi_s^2 \bar{y}_{pos}$ is a cohort-specific control for the average exposure-weighted outcome in the origin, ζ_m^1 is an age-at-move fixed effect, and $\zeta_m^2 p_i$ is an interaction of the age-at-move fixed effects with parental income rank. The key parameters of interest are the b_m coefficients, which capture how children’s outcomes vary with the age at which they move to an area with higher or lower predicted earnings. The intuition underlying this specification is discussed in Chetty and Hendren (2018a); further details of the sample specification and estimation methodology are provided in Online Appendix E of this paper.

Identification Assumptions. We can interpret differences in the coefficients b_m , e.g. $b_m - b_{m+1}$, as the causal effect of exposure to a better area (i.e., an area with higher observed incomes) under the assumption that the potential outcomes of children who move to better vs. worse areas do not vary with the age at which they move. Chetty and Hendren (2018a) present a series of tests supporting this orthogonality condition: controlling for unobserved heterogeneity across families using sibling comparisons in models with family fixed effects, implementing a set of placebo tests exploiting heterogeneity in predicted causal effects across subgroups, and validating the results using experimental designs, e.g. from the Moving to Opportunity Experiment (Chetty et al. 2016). Building on these results, we take the validity of the research design as given here and use it to explore racial heterogeneity in the causal effects of neighborhoods.

Results. Panels A and B of Figure XV plot the coefficients, b_m , for the specification in equation (7) using individual income ranks at age 30 for black and white males, respectively.⁴⁰ Consistent with the results in Chetty and Hendren (2018), we find declining coefficients b_m until approximately age 23, after which the coefficients are flat. Under the identification assumption described above, this result implies that neighborhood have causal effects on children’s outcomes in proportion to childhood exposure prior to age 23. We estimate that every year of childhood a black boy spends in a place where black boys grow up to have 1 percentile higher incomes increases his own income by 0.027 percentiles. The corresponding estimate for white males is 0.026 per year of exposure. Extrapolating over 20 years of childhood exposure, this estimate implies that children who move

⁴⁰We present analogous estimates for females in Online Appendix Table XIV.

at birth to an area where we observe 1 percentile higher incomes for children of their race would pick up roughly 50% of that effect themselves through a causal effect of place.

Panels C and D of Figure XV replicate Panels A and B using incarceration as the dependent variable and race-specific incarceration rates for \bar{y}_{pls}^r and Δ_{odps}^r in (7). Black boys are 0.033 pp more likely to be incarcerated for every year of childhood exposure to a place with 1 pp higher incarceration rates for black males. We find a slightly smaller exposure slope of 0.025 for white males.

Table IV presents an estimate of the slope of the coefficients by replacing the age-at-move fixed effects $\{b_m\}$ with a linear parametrization of age at move, separately for $m > 23$ and $m \leq 23$. Columns 1-4 show that this specification yields estimates analogous to those in Figure XV for income and incarceration. Columns 5-6 report estimates of exposure effects for marriage. Every year of exposure to a CZ in which black males are 1pp more likely to be married at age 30 increases a black boy's likelihood of being married at age 30 by 0.023 pp. We find a nearly identical effect of 0.023 pp for white males.

These results above show that places have causal effect on the levels of children's outcomes in adulthood; but do they have causal effects on the intergenerational gap across races? That is, if a black and white male both spend an additional year of childhood in a place where we observe a larger black-white gap, do we find differential effects on their outcomes?

To test for effects on racial gaps, Columns 7-12 of Table IV present results from an expanded specification that predicts the outcomes of black movers using not only the outcomes of black male children but also the outcomes of white children (and vice versa for white movers). Column 7 shows that we find a slope on the incomes of black males of -0.029 (s.e. 0.004), similar to the slope of -0.027 in the baseline specification. In contrast, we find a slope of -0.003 (s.e. 0.004) for the white males' outcomes. Hence, conditional on the outcomes of black males, the outcomes of white males in the destination CZ are not predictive of the black child's income in adulthood. Column 8 shows that the converse is true white males. We estimate a slope of -0.023 (s.e. 0.002) on the difference in income ranks of white males, but a coefficient of -0.004 (s.e. 0.001) on the difference in income ranks of black males. Columns 9-12 document analogous patterns for incarceration and marriage.

We conclude based on this analysis that much of the observational variation in black-white intergenerational gaps documented above reflects the causal effects of environment rather than selection. In establishing the importance of environmental factors, this finding rejects the hypothesis

that racial gaps are driven entirely by differences in immutable traits such as innate ability.

The finding that neighborhood effects on racial gaps are proportion to *childhood* exposure is consistent with prior evidence documenting the emergence of racial gaps in achievement in childhood (Fryer and Levitt 2004) and the fact that pre-labor-market measures explain a large fraction of racial gaps in labor market outcomes (Neal and Johnson 1996; Altonji and Blank 1999; Fryer 2010). It is also consistent with evidence from the Moving to Opportunity experiment showing that moving to a different neighborhood in adulthood has little impact on income, whereas moving as a young child improves outcomes, for both blacks and whites (Chetty et al. 2016).

VII.D Summary: Environment Matters, but Good Environments are Rare

The analysis in this section has shown that childhood environment has significant causal effects on black-white gaps. Black boys do especially well in neighborhoods with a large fraction of fathers at home in black families and low levels of racial bias among whites. However, very few black boys grow up in such areas in the U.S. 4.2% of black children currently grow up in areas with a poverty rate below 10 percent and more than half of black fathers present (Figure XVI).⁴¹ In contrast, 62.5% of white children grow up in low-poverty areas with more than half of white fathers present. These disparities in the environments in which black and white children are raised help explain why we observe significant black-white gaps in intergenerational mobility in virtually all areas of the U.S.

VIII Conclusion

Differences in intergenerational mobility are a central driver of racial disparities in the U.S. Black and American Indian children have substantially lower rates of upward mobility and higher rates of downward mobility than white children. The gap in incomes between blacks and American Indians relative to whites is thus likely to persist indefinitely without changes in their rates of intergenerational mobility. In contrast, Hispanics have relatively high rates of absolute upward mobility and are moving up significantly in the income distribution across generations, despite having incomes similar to blacks today.

The black-white gap – the largest gap among those we study – is driven entirely by sharp differences in the outcomes of black and white men who grow up in families with comparable

⁴¹Examples of these neighborhoods are given in Online Appendix Table XV. We do not cut on racial bias in this analysis because of the lack of data on racial bias at the tract level; doing so would only further reduce the number of “good” neighborhoods for black children.

incomes. Although closing this gap may appear to be a daunting challenge given its persistence, there are some encouraging signs that the problem can be solved. First, black children have rates of relative mobility comparable to whites: they are not stuck at the same income levels as their parents. Closing the gap in opportunities between black and white children at a given parental income level could therefore eliminate much of the black-white income gap within two generations. Second, the black-white gap is significantly smaller for boys who grow up in certain neighborhoods – those with low poverty rates, low levels of racial bias among whites, and high rates of father presence among low-income blacks. Black boys who move to such areas at younger ages have significantly better outcomes, demonstrating that racial disparities can be narrowed through changes in environment.

The challenge is to replicate the conditions that lead to these smaller disparities more broadly across the country. Our findings suggest that many widely discussed proposals may be insufficient to narrow the black-white gap in the long run. Policies focused on improving the economic outcomes of a single generation – such as cash transfer programs or minimum wage increases – can narrow the gap at a given point in time, but are less likely to have persistent effects unless they also affect intergenerational mobility. Policies that reduce residential segregation or enable black and white children to attend the same schools without achieving racial integration within neighborhoods and schools would also likely leave much of the gap in place, since the gap persists even among low-income children raised on the same block.

Instead, our results suggest that efforts that cut *within* neighborhoods and schools and improve environments for specific racial subgroups, such as black boys, may be more effective in reducing the black-white gap. Examples include mentoring programs for black boys, efforts to reduce racial bias among whites, or efforts to facilitate social interaction across racial groups within a given area (e.g., Devine et al. 2012; Heller et al. 2015). Our analysis does not offer guidance on which interventions of this type are most effective, but calls for greater focus on and evaluation of such efforts.

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ONLINE APPENDICES

A. Data Construction

This appendix provides further details on the methods we use to construct our analysis sample and assign individuals to Census blocks.

Sample Construction. We begin with the set of children born between 1978 and 1983, based on birth dates recorded in the Numident file (22.8 million children), which contains records on all persons in the U.S. who have ever had a Social Security Number (SSN). For each child, we define the parent(s) as the first person(s) who claim the child as a dependent on a 1040 tax form. If parents are married but filing separately, we assign the child to both parents. To eliminate dependent claiming by siblings or grandparents, in the case of a potential match to married parents or single mothers, we require that the mother be 15-50 at the birth of the child. In the case of children claimed by a single father, we require that he be between 15-50 at the birth of the child.⁴² If no such eligible match occurs in 1994, the first year of the data in which we have dependent claiming information, we search subsequent years through 2015 until a valid match is found.

Once we match a child to parents, we hold this definition of parents fixed regardless of subsequent dependent claims or changes in marital status. For example, a child matched to married parents in 1996 who divorce in 1997 will always be matched to the two original parents. Conversely, a child matched to a single parent in 1996 who marries in 1997 will be considered matched to a single parent, though spouse income will be included in our definition of parent income because we measure parent income at the family level in our baseline analysis.

We exclude children whose mean real or nominal parent income is zero or negative (1.0% of children) because parents who file tax returns (as is required to link them to a child) reporting negative or zero income typically have large capital losses, which are a proxy for having significant wealth. We construct a strongly balanced sample of children by assigning incomes of zero to children who do not appear in the tax data (e.g., because they have died). We then assign children and parents income percentile ranks on the sample of children linked to parents with positive income, using the income definitions described in Section II.B. Finally, we restrict the sample to individuals who have non-missing race information to obtain our final analysis sample. Note that this ordering of operations implies that we rank children and parents relative to all individuals in the sample, not just those with non-missing race information.

Assignment of Children to Census Tracts. Addresses in the tax records are geocoded and assigned to standard Census geographic units (e.g. block, tract, and county) by Census staff in the Census Master Address File (MAF). The geocoding process involves cleaning address information so that it can be merged on to the MAF and assigned a MAFID, which is then associated with the geographic units that we use. Brummet (2014) describes this process in greater detail. Brummet also reports statistics on the match rate for addresses; for example, 92% of addresses in the 2009 American Housing Survey were successfully matched to the MAF.

We assign children to Census tracts (or other geographies) where they grew up based on the address from which their parents filed 1040 tax forms and claimed them as dependents. In particular, we identify all the Census tracts from which their parents filed tax returns (between 1989-2015)

⁴²Children can be claimed as a dependent only if they are aged less than 19 at the end of the year (less than 24 if enrolled as a student) or are disabled. A dependent child is a biological child, step child, adopted child, foster child, brother or sister, or a descendant of one of these (for example, a grandchild or nephew). Children must be claimed by their custodial parent, i.e. the parent with whom they live for over half the year. Furthermore, the custodial parent must provide more than 50% of the support to the child. Hence, working children who support themselves for more than 50% cannot be claimed as dependents. See IRS Publication 501 for further details.

during or before the year in which their child turned 23. Beginning in 2003, we use address data from information returns (e.g., W-2 forms) for non-filers. Since we search for address information in multiple years, we are able to assign 99.5% of children in our baseline sample to at least one non-missing tract during their childhood. We use an analogous process to assign children to geographies when they are adults in 2015, using their own 1040 form or, for non-filers, address data from information returns (e.g., W-2 forms).

B. Comparison to Survey Datasets

In this appendix, we assess the representativeness of our analysis sample by comparing sample counts and descriptive statistics to corresponding measures from publicly available survey datasets. We conduct three sets of analyses.

First, we assess the coverage rate of our analysis sample by comparing the number of children in our analysis sample to the number of individuals in the ACS who were born in the U.S. or came to the U.S. before age 16. Appendix Table II shows that the total number of children whom we link to parents is comparable to the expected number of children based on the ACS (using the ACS sampling weights). On average over the 1978-83 birth cohorts, our sample count of children linked to parents with positive income is 99.6% as large as that in the ACS.⁴³ Information on race and ethnicity is available for 94.1% of children; we lose 6% of the sample because their records in the Census could not be assigned a PIK (i.e., linked to the Numident file) based on the information provided. The coverage rates are above 94% for all racial and ethnic subgroups except for Hispanics, for whom our sample count is 78.9% of that in the ACS. This is primarily because our sample includes only authorized immigrants, whereas the ACS covers all immigrants.⁴⁴ Lopez and Radford (2017) estimate that approximately 17.7% of immigrants in the United States in 1990 were unauthorized, suggesting that our sample covers approximately $78.9/82.3 = 95.9\%$ of Hispanics who are authorized immigrants or citizens, similar to rates of coverage for other groups.

Next, in Appendix Table III, we examine whether the characteristics of individuals in our analysis sample are representative of the corresponding population in the ACS. We start from individuals in the 1978-83 birth cohorts who appear in the 2015 ACS and report their mean individual income ranks and other characteristics (based on the ACS data) for three samples: all individuals who appear in the ACS (Column 1), those who appear in both the ACS and our analysis sample (Column 2), and those who appear in the ACS but not our analysis sample (Column 3). Mean income ranks differ by 1 percentile or less between our analysis sample and the full ACS sample for all groups except Hispanics, for whom there is a larger discrepancy because our sample does not include unauthorized immigrants as noted above. Mean income ranks are slightly higher for those in our analysis sample than in the complement, which is because individuals who have particularly low incomes are less likely to appear in Census and tax data and hence are less likely to be in our linked data. We find similar results for other variables such as marriage rates and college attendance.

Finally, we assess whether the income measures and other statistics we construct from the linked Census-tax records are representative of corresponding measures in publicly available survey data. In Appendix Table IV, we report summary statistics on income distributions (Panel A) and

⁴³These comparisons are not exact because there are small differences between our sample definitions and the ACS. As discussed in Section III, our sample does not include unauthorized immigrants, whereas the ACS does, a factor that reduces our counts relative to the ACS. In the other direction, (1) we retain individuals who have died by 2015 whereas the ACS does not; (2) we retain individuals who were ever in the U.S. but left by 2015, whereas the ACS does not; and (3) some children may have immigrated to the U.S. after age 16 and still be claimed as dependents by parents.

⁴⁴The ACS does not ask about immigration status, preventing us from comparing counts of authorized immigrants directly.

demographics (Panel B) for five different samples. The first two columns use the (publicly available) 2012-2016 Current Population Survey (CPS) and 2012-2016 ACS, focusing on individuals in the 1978-83 birth cohorts who were born in the U.S. or came to the U.S. before age 16. Column 3 uses data from the 2015 ACS who appear in our analysis sample, and measures their incomes and other characteristics in the ACS data. As shown in Appendix Table III, the individuals in the linked analysis sample have slightly higher incomes than those in the ACS in general, with a median income of \$33,860 vs. \$32,810 in the publicly available ACS and \$33,000 in the CPS.

Column 4 uses the same sample as Column 3, but reports income data from the tax records. Income distributions measured in the tax records are very well aligned with the ACS. For example, median income is \$33,340 when measured in the tax data and \$33,860 in the ACS data holding the sample of individuals fixed. Column 5 assesses the extent to which estimates of income in tax records are biased due to non-filing. It shows statistics on income and other characteristics using ACS data for individuals who appear in both the ACS and the analysis sample, but who have zero income in the tax data in 2015 (i.e., those who have no 1040 or W-2 forms in 2015). The median income of these individuals is \$5,000 in the ACS, showing that individuals we assign zero income based on tax records typically have very low incomes in survey data as well. Hence, the tax records do not miss substantial amounts of income for non-filers.

In sum, comparisons to nationally representative surveys show that our analysis sample provides an accurate representation of our target population in terms of overall coverage rates and sample characteristics and that the tax records provide valid measures of income.

C. Construction of Tract-Level Covariates

This appendix provides definitions and sources for the covariates used in Section VII.B. Our source data are primarily at the tract level; all data obtained at other geographies were collapsed to the tract level (with the exception of measures of racial bias, which are only available at broader geographical levels). We use 2010 Census tract definitions throughout. For covariates defined using 2000 tract boundaries, we use the 2010 Census Tract Relationship Files from the [US Census Bureau](#) to crosswalk 2000 tracts to 2010 tracts, weighting the 2000 tract-level covariates by the fraction of the 2010 tract population that lives within the 2000 tract boundaries.

We organize the covariates using the categories used in Appendix Table X.

Economy. We calculate the share of individuals below the poverty line for all individuals and by race in each tract using tables NP087B and NP159B of the [National Historical Geographic Information System \(NHGIS\) database](#) (2000 Census long form SF3a). To estimate the mean household income for each tract, we use data on the distribution of households in 16 income bins from table NP052A of the [NHGIS database](#) (2000 Census long form SF3a). We assume that the mean household income in each bin equals the middle of the bin and impute a mean value of \$300,000 for the highest income bin (\$200,000 or more). We then calculate the mean household income for each tract using the distribution of households over income bins in the tract. We obtain employment rates by race and sex in each tract using table NP150E of the NHGIS database (2000 Census long form SF3a). We define the share working in manufacturing as the number of workers employed in the manufacturing industry over the total number of workers (in the sample of people who are 16 years and older). These data are from table NP049C of the [NHGIS database](#) (2000 Census long form SF3a).

Schools. Data for 3rd and 8th grade test scores are downloaded from the [Stanford Education Data Archive](#) (table MeanA_V1.1) and measured at the district level. We create a crosswalk from districts to tracts by weighting by the proportion of land area that a given school district covers in a tract. Data on suspension rates are downloaded from the [Office for Civil Rights \(OCR\) Data](#)

Collection tool using the 2013 Discipline and Disability data tables at the school-level for all states. We restrict to high schools with at least 500 students. Where possible, schools are crosswalked to school catchment areas; then school catchment areas are crosswalked to tracts.

Health. The share without health insurance is constructed using tract-level data from table B27001 of the American Community Survey (2008-2012) using the [NHGIS database](#) by subtracting the number of people ages 18-64 with health insurance from the total tract-level population and then dividing this number by the total tract-level population.

Family Structure. We define the share of single parents in each tract as the number of households with female heads (and no husband present) or male heads (and no wife present) with own children under 18 years old present divided by the total number of households with own children present. The data come from tables NP018E and NP018G of the [NHGIS database](#) (2000 Census short form SF1a). We calculate the share married and share divorced in each tract using the number of people who are married or divorced (in the sample of people who are 15 years and older) using data from the [NHGIS database](#) in table NPCT007C (2000 Census long form SF3a). We estimate the share of children born to low-income parents growing up in a household with father present by race in each tract using our own Census microdata analysis sample. We first regress an indicator variable for whether a child was matched to a father (see Online Appendix A) on a child's parent income percentile for each tract and race using our analysis sample (children in the 1978-83 birth cohorts). We then use the predicted value at the 25th percentile of the parent income distribution as the estimate for each tract and race group. We estimate the share of children born to low-income parents growing up in a household with a mother present by race and tract analogously.

Demographics. The demographic variables are constructed from tract-level Census data using the [NHGIS database](#). The share of black residents is defined as the share of non-Hispanic black residents who listed "Black" as their only race or as one of multiple races in the 2010 Census (long form SF1, table H73). The share of the population younger than 18 is defined as the number of persons under 18 in the 2000 Census divided by the total tract-level population (long form SF1a, table NP012B). The share foreign born is defined as the number of foreign born residents in the 2000 Census divided by the sum of native and foreign born residents (long form SF3a, table NP021A).

Education. The education variables are constructed from tract-level 2000 Census data using the [NHGIS database](#) (long form SF3, table NP037C). The share that have less than a high school education is calculated by dividing the number of people over 25 who did not graduate from high school by the total number of people over 25 in a tract. The share of college educated is calculated by dividing the number of people over 25 who have a bachelor's degree, master's degree, professional school degree, or doctorate degree over the total number of people over 25 in a tract.

Housing. The housing variables are constructed from tract-level Census and ACS data using the [NHGIS database](#). Population density is calculated by dividing the total tract-level population in the 2000 Census by the land area of 2010 Census tract boundaries measured in square kilometers (long form SF1a, table NP001A). The share who own homes is calculated by dividing the number of housing units owned in the 2000 Census by the total number of housing units in a tract (long form SF1a, tables H1 and H4). The median two-bedroom rent variable is constructed from tract-level ACS data (2011-2015) and is defined as the median gross rent for renter-occupied housing units with two bedrooms that pay cash rent (table AD79). The black median home value variable is defined as the median value of owner-occupied housing units for black homeowners in the 2000 Census; white median home value is defined analogously for whites (long form SF3a, tables NHCT042A and NHCT042C).

Racial Bias. We construct racial bias measures using three data sources. Implicit Association Test (IAT) scores were obtained from the Race Implicit Association Database, available at [Journal of Open Psychology](#). The IAT score is a measure of racial bias that is constructed by measuring

the difference in a participant’s ability to match positive and negative words with black vs. white faces, where higher IAT scores represent more implicit bias toward black faces (Greenwald et al. 1998). We calculate mean IAT racial bias scores for white and black study participants at the county level, pooling data from 2003-2016.

The Racial Animus Index is obtained from Stephens-Davidowitz (2014), available at [racially charged searches](#). It is a measure of the frequency of racially charged Google searches at the media market level, which are aggregations of counties.

The interracial marriage attitude data are constructed by Mas and Moretti (2009) using publicly available data from the General Social Survey. They measure the fraction of white voters who support anti-interracial-marriage laws, tabulated by state.

D. Evolution of Racial Disparities with Gender Heterogeneity

This appendix extends the model developed in Section II to show how racial disparities evolve when racial gaps in intergenerational mobility differ by gender.

For simplicity, we ignore marital patterns and assume that each family i consists of a man and a woman in each generation. We model the individual income of a person of gender $g \in \{m, f\}$ in family i in generation t as

$$y_{it}^g = \alpha_r^g + \beta_m y_{i,t-1}^m + \beta_f y_{i,t-1}^f + \varepsilon_{igt}$$

where $y_{i,t-1}^g$ denotes the individual income of a parent of gender g , and ε_{igt} denotes an idiosyncratic shock that is independent across generations and genders and has expectation $E[\varepsilon_{igt}] = 0$. Note that we assume that relative mobility (β_m, β_f) does not vary across races in this specification, consistent with our empirical findings.

In steady-state, the mean rank of each gender satisfies $\bar{y}_{it}^g = \bar{y}_{i,t-1}^g$. The steady state mean income rank for individuals of gender g and race r is given by:

$$\bar{y}_r^g = \frac{(1 - \beta_{-g})\alpha_r^g + \beta_{-g}\alpha_r^{-g}}{1 - \beta_r^m - \beta_r^f},$$

where $-g$ denotes the other gender, i.e., $-g = m$ if $g = f$.

If $\Delta\alpha^f = \alpha_w^f - \alpha_b^f = 0$, as we find empirically, then the black-white gap for women in the steady state is directly proportional to the intergenerational black-white gap for men, $\Delta\alpha^m$:

$$\Delta\bar{y}^f = \frac{\beta_m}{1 - \beta_m - \beta_f} \Delta\alpha^m.$$

E. Estimating Causal Effects of Neighborhoods: Methodology

In this appendix, we document the sample, variable construction, empirical specifications used in Section VII.C.

Sample and Variable Construction. Our core sample and data construction is the same as that described in Section III, but expands in two directions that increase our ability to observe moves at younger ages. First, we extend our analysis to include the 1978-1986 cohorts. Second, we include income ranks measured at age 30, in addition to ranks of pooled incomes over ages 31-37 in our analysis above.⁴⁵ Chetty et al. (2014) shows that although children’s incomes from different backgrounds are continuing to diverge in levels, changes in a child’s income rank after age 30 (relative to their cohort peers) are no longer significantly correlated with their parental

⁴⁵Because we do not observe income at age 30 for the 1986 cohort, our income and marriage at age 30 analysis will use only the 1978-1985 sample. We include the 1986 cohort in our analysis of incarceration.

background. Lastly, we also consider specifications for household income ranks at age 24 pooling across genders and races, as in Chetty and Hendren (2018a). For this, we use an expanded sample of the 1978-1991 cohorts.

Using the location of each child’s parents in each year in our sample, we form a sample of 1-time movers. These are defined as children whose parents move across CZs exactly once when they are age 28 or below.⁴⁶ We define the year of the move as the tax year in which the parents report living in a different CZ relative to the previous year. In cases where we do not observe sequential years of location information (e.g. we do not observe 1990-93 and 1996-97), we assign the year of move as the midpoint between the two nearest years in which different addresses are reported (e.g. if we see a new location in 1994 relative to 1989, we assign the year of move to be 1992.5). In cases where this leads to a non-integer year of move, we randomly select the nearest year for the move. We then define the child’s age at the time of the move as the year of the move minus the child’s cohort.

Following Chetty and Hendren (2018a), we make three additional sample restrictions. First, we restrict to moves between destinations and origins that have at least 25 observations used to calculate \bar{y}_{pos} and \bar{y}_{pds} . As shown in Online Appendix A of Chetty and Hendren (2018a) imposing such sample restrictions limits the impact of attenuation bias from sampling error in the \bar{y}_{pcs} estimates.⁴⁷ Second, we require that we are able to observe the parents for at least two years after the move in order to enter the sample (e.g. for a child born in 1991 we only consider moves through 2013, since s/he is observed until 2015). Third, we require families to move at least 100 miles. This ensures that the children’s environments are actually changing and helps rule out cases where families move at short distances but happen to cross CZ boundaries. Appendix Table XIII presents summary statistics for the one-time movers sample and the complementary exposure-weighted sample. In the one-time movers sample, we have a total sample size of roughly 152,000 black male children and 887,000 white male children for whom we observe income at age 30.

For each subgroup of the analysis, g (e.g. g could represent black males, white females, etc), we use the remaining sample of children whose parents are observed in exactly one or 3+ CZs to provide an estimate of the average outcomes of children in group g who grew up in each CZ. Using this sample, we restrict to those in group g and construct exposure-weighted outcomes, \bar{y}_{pcs} , for each location c , race r , and parental income p using the procedure described in Section VII.B. We take children observed in each CZ in the subgroup and regress their outcomes on a linear term in parental income rank, weighting by the number of years below age 23 in which the parents are observed in the CZ. We let \bar{y}_{pcs} denote the predicted value from this regression for a child at parental income rank p .

Empirical Specification. Using the sample of 1-time movers, we consider the outcomes of child i with parental income rank p_i who moved at age m_i from origin CZ, o , to destination CZ, d . We regress the child’s outcome, y_i using a specification analogous to the approach in Chetty and Hendren (2018a). Let \bar{y}_{pcs} denote the exposure-weighted outcome of y_i for children who grew up in CZ c with parental income rank $p = p_i$. Let $\Delta_{odps} = \bar{y}_{pds} - \bar{y}_{pos}$ denote the difference in the income rank of exposure-weighted residents in the destination versus origin for children in cohort s with parental income rank p . We run a regression of the form noted in the main text:

⁴⁶When constructing the sample, we observe location up to age 30. But, as discussed below, we follow Chetty and Hendren (2018a) and require that we observe the parents in the destination for at least two years. Therefore, the oldest age of move for the parents is 28.

⁴⁷Chetty and Hendren (2018) use population restrictions of 250,000 in the 2000 Census. We instead use count restrictions on \bar{y}_{pcs} because many of our specifications focus on subsamples of the data (e.g. black males).

$$\begin{aligned}
y_{i,c} = & \sum_{s=1978}^{1986} I(s_i = s)(\phi_s^1 + \phi_s^2 \bar{y}_{pos}) + \sum_{m=2}^{28} I(m_i = m)(\zeta_m^1 + \zeta_m^2 y_{i,p}) \\
& + \sum_{m=2}^{28} b_m I(m_i = m) \Delta_{odps} + \varepsilon_{1i},
\end{aligned} \tag{8}$$

where ϕ_s^1 is a cohort-specific intercept, $\phi_s^2 \bar{y}_{pos}$ is a control for the average exposure weighted outcome in the origin in which the coefficient is allowed to vary by cohort. These control for the selection of the origin in which children are coming from. Next, ζ_m^1 is an intercept and $\zeta_m^2 y_{i,p}$ is an interaction with parental income rank that vary with the child's age at the time of the move, m . These control for heterogeneous disruption or selection effects that may occur with moves at different ages. Finally, the coefficients, b_m , provide an estimate the exposure effect. The exposure effect at age m is given by $b_m - b_{m+1}$. How the b_m coefficients vary with the child's age at the time of the move, m , capture the effect of moving at age m instead of $m + 1$ to a CZ in which children have 1-unit higher outcomes.⁴⁸

In addition to allowing the coefficients b_m to vary for each age, m , we also follow Chetty and Hendren (2018a) by estimating a linear parametrization of these coefficients over the age ranges above and below 23. This specification is given by:

$$\begin{aligned}
y_{i,c} = & \sum_{s=1978}^{1986} I(s_i = s)(\phi_s^1 + \phi_s^2 \bar{y}_{pcs} + \phi_s^3 \bar{y}_{pcs}^r) + \sum_{m=2}^{28} I(m_i = m)(\zeta_m^1 + \zeta_m^2 y_{i,p}) \\
& + 1 \{m_i \leq 23\} (\delta_{\leq 23} + m \gamma_{\leq 23}) \Delta_{odps} + 1 \{m_i > 23\} (\delta_{> 23} + m \gamma_{> 23}) \Delta_{odps} + \varepsilon_{2i},
\end{aligned} \tag{9}$$

To test whether the race-specific differences in observed outcomes partially reflects the causal effect of childhood exposure, we add the outcomes of the other race to the regression in equation (9):

$$\begin{aligned}
y_{i,c} = & \sum_{s=1978}^{1986} I(s_i = s)(\phi_s^1 + \phi_s^2 \bar{y}_{pcs} + \phi_s^3 \bar{y}_{pcs}^r) + \sum_{m=2}^{28} I(m_i = m)(\zeta_m^1 + \zeta_m^2 y_{i,p}) \\
& + 1 \{m_i \leq 23\} (\delta_{\leq 23} + m \gamma_{\leq 23}) \Delta_{odps} + 1 \{m_i > 23\} (\delta_{> 23} + m \gamma_{> 23}) \Delta_{odps}, \\
& + 1 \{m_i \leq 23\} (\delta_{\leq 23}^r + m \gamma_{\leq 23}^r) \Delta_{odps}^r + 1 \{m_i > 23\} (\delta_{> 23}^r + m \gamma_{> 23}^r) \Delta_{odps}^r + \varepsilon_{3i},
\end{aligned} \tag{10}$$

where \bar{y}_{pcs}^r and Δ_{odps}^r are the outcomes of white (black) children when running a regression on the sample of black (white) children.

⁴⁸Equation (8) is identical to the baseline specification in equation (6) of Chetty and Hendren (2018), with the exception that we do not include a cohort-varying intercept term, $\sum_{s=1980}^{1988} \kappa_s^d \Delta_{odps}$. We make this modification because below we will apply the specification to the smaller subsample of black males. With few observations in some cohorts, including these terms introduces additional noise in the estimates. Chetty and Hendren (2018) verify that the exclusion of these interactions does not meaningfully affect their results.

Table I
Statistics on Income Disparities and Intergenerational Mobility by Racial Group

	White			Black			Asian			Hispanic			American Indian		
	Pooled	Male	Female	Pooled	Male	Female	Pooled	Male	Female	Pooled	Male	Female	Pooled	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
<i>A. Individual Income</i>															
Median Income (\$)	33,620	40,710	26,580	19,550	18,220	20,400	43,690	45,550	41,730	27,140	32,250	22,930	16,610	19,030	14,870
Mean Percentile Rank	53.3	58.4	47.9	42.0	40.8	43.1	60.3	61.5	59.0	48.1	51.7	44.5	39.6	42.0	37.3
P(Child in Q1 Parent in Q1)	28.1%	26.0%	30.3%	28.7%	37.5%	20.5%	17.5%	17.0%	18.0%	23.2%	23.5%	22.8%	37.8%	39.0%	36.6%
P(Child in Q5 Parent in Q1)	11.1%	14.8%	7.2%	6.3%	7.4%	5.2%	26.8%	28.0%	25.6%	10.8%	14.8%	6.7%	5.3%	7.4%	3.3%
P(Child in Q1 Parent in Q5)	11.7%	8.7%	14.9%	13.8%	16.4%	11.0%	11.3%	10.8%	11.9%	13.3%	11.6%	15.1%	18.2%	16.2%	20.3%
P(Child in Q5 Parent in Q5)	36.9%	45.2%	28.2%	26.2%	27.0%	25.4%	49.9%	52.8%	46.9%	31.4%	37.5%	25.4%	24.1%	28.7%	19.1%
<i>B. Household Income</i>															
Median Income (\$)	53,730	51,960	55,740	20,650	17,730	22,690	63,720	56,580	71,880	35,180	35,280	35,080	22,260	20,890	23,450
Mean Percentile Rank	55.7	54.5	56.8	34.8	32.6	36.8	60.7	57.5	63.9	45.6	44.6	46.7	36.7	35.7	37.8
P(Child in Q1 Parent in Q1)	29.0%	31.3%	26.7%	37.3%	48.5%	26.8%	16.7%	19.9%	13.2%	24.8%	29.1%	20.4%	45.5%	49.3%	41.7%
P(Child in Q5 Parent in Q1)	10.6%	9.7%	11.5%	2.5%	2.5%	2.6%	25.5%	21.2%	30.1%	7.1%	6.6%	7.6%	3.3%	3.1%	3.5%
P(Child in Q1 Parent in Q5)	8.7%	10.0%	7.3%	16.7%	21.5%	11.8%	9.9%	11.9%	8.0%	12.0%	14.0%	10.0%	18.8%	20.9%	16.6%
P(Child in Q5 Parent in Q5)	41.1%	39.3%	43.0%	18.0%	17.4%	18.6%	48.9%	45.6%	52.2%	30.6%	28.8%	32.4%	23.0%	21.5%	24.6%
Median Parent Household Income	55,810			29,200			53,010			33,060			34,850		
Mean Parent Household Income Rank	57.9			32.7			49.2			36.2			36.8		
Steady-state Household Income Rank	54.4			35.2			62.9			48.7			36.5		
Number of obs (1000's)	13,490	6,891	6,599	2,750	1,348	1,402	685	350	335	2,615	1,312	1,303	165	84	82

Notes: This table describes individual and householding income and intergenerational mobility by race and gender for children in our sample. All racial groups except Hispanics exclude individuals of Hispanic ethnicity. Panel A presents descriptive statistics on individual income by race and gender. Panel B presents the same statistics for household income. All statistics are based on the primary analysis sample (children in the 1978-83 birth cohorts) and baseline income definitions for parents and children (see Section III). All values in this and all subsequent tables and figures have been rounded to four significant digits as part of the disclosure avoidance protocol. Counts are rounded in the following manner: numbers between 10,000 and 99,999 are rounded to the nearest 500; between 100,000 and 9,999,999 to the nearest 1,000 and above 10,000,000 to the nearest 10,000. Sources for this and all subsequent tables and figures: authors calculations based on Census 2000 and 2010, tax returns, and American Community Surveys 2005-2015.

Table II
Association Between Black Father Presence and Black Boys' Outcomes: OLS Regression Estimates

	Baseline	Black and White Father Present	State FE	Father Absent	Two Parents	All Tracts	Black Fathers per Child	Gender Ratio	Current Tract FE
Dependent Variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low-Income Black Father Presence	0.0492 (0.0062)	0.0450 (0.0068)	0.0501 (0.0066)	0.0279 (0.0108)	0.0461 (0.0128)	0.0806 (0.0036)			0.1052 (0.0079)
Low-Income White Father Presence		0.0077 (0.0076)							
Low-Income Black Father Presence in 2000							0.0382 (0.0043)	0.0387 (0.0043)	
Low-Income Black Male Filers Per Child								-0.0011 (0.0011)	
Low Poverty Tracts	X	X	X	X	X				
State FE's			X						
Current Tract FE's									X
R2	0.007	0.007	0.070	0.002	0.002	0.020	0.009	0.009	0.239
Number of Tracts	10,582	10,444	10,582	5,159	5,280	28,850	10,177	10,177	
Number of Observations									193,000

Notes: This table presents coefficients from a regression of the average income rank of black males who grow up in each census tract in below median income families (p25). Column 1 presents the baseline regression of these outcomes in each tract on the fraction of low-income black fathers present. Column 2 adds in a control for low-income white fathers presence. Column 3 adds state fixed effects. Column 4 replaces the dependent variable with the complementary subset of children in families with no father present. Column 5 replaces the dependent variable with one calculated using the subsample of children in households with married parents. Column 6 considers the baseline specification in column 1 but includes all available tracts instead of imposing a restriction to low-poverty census tracts. Column 7 replaces the independent variable with the number of low-income black fathers per child regardless of whether they are in the household, Column 8 adds an additional regressor as the number of low-income black filers per child. Column 9 is run at the individual level and adds fixed effects for the tract in which children currently reside when their adult incomes are measured to the specification in Column 6. See Appendix C for further details on variable constructions. Note that all observation counts shown are rounded as described in the notes to Table I.

Table III
Association Between Racial Bias Among Whites and Black Children's Outcomes: OLS Regression Estimates

Sample:	Black Male	Black Male	Black Male	Black Male	Black Male	Black Female	White Male	Black Male	Black Male	Black Male	Black Female	White Male
Dependent Variable:	Individual Income	Individual Income	Individual Income	Employed	Incarcerated	Individual Income	Individual Income	Individual Income	Employed	Incarcerated	Individual Income	Individual Income
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Difference in IAT	-0.0081 (0.0024)		-0.0060 (0.0019)	-0.0052 (0.0022)	0.0039 (0.0032)	-0.0082 (0.0029)	-0.0097 (0.0025)					
IAT White		-0.0080 (0.0023)										
IAT Black		0.0047 (0.0023)										
Racial Animus								-0.0263 (0.0056)	-0.0138 (0.0057)	0.0278 (0.0092)	-0.0191 (0.0080)	-0.0203 (0.0042)
State FE's			X									
Geography of Analysis	Counties	Counties	Counties	Counties	Counties	Counties	Counties	Media Markets	Media Markets	Media Markets	Media Markets	Media Markets
R2	0.033	0.042	0.592	0.017	0.005	0.025	0.042	0.461	0.185	0.277	0.185	0.469
Number of Counties/Media Markets	340	340	340	340	312	325	340	28	28	26	27	28
Number of Observations	492,200	492,200	492,200	492,200	353,000	491,700	492,200	386,600	386,600	277,900	386,600	386,600

Notes: This table shows the relationship between measures of racial bias at the county/media market level and outcomes for children who grow up in those areas. All the measures of racial bias are standardized. See Appendix C for a precise definition and sources of the Implicit Association Bias (IAT) and Racial Animus. IAT measures are only available by county, so we aggregate the outcomes at p25 in each tract to the county or media market level using weighting by the number of children observed in each tract. We restrict to counties media markets with poverty rates less than 10% obtained by aggregating the tract-level poverty rates up to the county level using population weights from the 2000 Census. Columns 1-7 present county-level regressions using the IAT measure. Column 1 regresses black male individual incomes for children in p25 families on the difference in the IAT for white versus black respondents. Column 2 includes separate regressors for black and white respondents. Column 3 adds state fixed effects to the specification in Column 1. Column 4 replaces the dependent variable with employment rates at p25, as opposed to individual income, and column 5 replaces the dependent variable with incarceration rates. Column 6 replaces the dependent variable with individual income for black females at p25. Column 7 replaces the dependent variable with individual income for white males. Columns 8-12 present media-market-level regressions using the Racial Animus measure. Column 8 presents the coefficient for individual income, column 9 replaces this with employment rates for black men in p25 families, column 10 replaces this with incarceration rates for black men in p25 families. Column 11 replaces the dependent variable with individual income for black females in p25 families, and column 12 replaces the dependent variable with individual income of white males in p25 families. Note that all observation counts shown are rounded as described in the notes to Table I.

Table IV
Quasi-Experimental Estimates of Neighborhood Causal Exposure Effects for Men

<i>Outcome:</i>	Exposure Effects Using Baseline Specification						Exposure Effects Using Other Race Placebos					
	Individual Income at		Incarcerated in 2010		Married at Age 30		Individual Income at		Incarcerated in 2010		Married at Age 30	
<i>Sample:</i>	Black Males	White Males	Black Males	White Males	Black Males	White Males	Black Males	White Males	Black Males	White Males	Black Males	White Males
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Own-Race Exposure Effect:	-0.027 (0.004)	-0.027 (0.002)	-0.034 (0.004)	-0.027 (0.003)	-0.023 (0.004)	-0.022 (0.001)	-0.029 (0.004)	-0.023 (0.002)	-0.032 (0.004)	-0.031 (0.004)	-0.017 (0.004)	-0.021 (0.002)
<u>Placebos:</u>												
Under-23 Other-Race Placebo							0.003 (0.004)	-0.004 (0.001)	-0.018 (0.014)	0.001 (0.001)	-0.015 (0.003)	-0.002 (0.002)
Over-23 Own-Race Placebo	0.008 (0.025)	-0.016 (0.011)	-0.030 (0.027)	-0.010 (0.023)	0.018 (0.029)	0.004 (0.010)	0.015 (0.029)	-0.025 (0.015)	-0.032 (0.030)	0.020 (0.033)	0.005 (0.030)	-0.005 (0.015)
Over-23 Other-Race Placebo							-0.013 (0.028)	0.005 (0.010)	0.012 (0.099)	0.004 (0.007)	0.034 (0.023)	-0.007 (0.011)
Num. of Obs.	150,000	884,000	123,000	712,000	150,000	884,000	150,000	668,000	122,000	460,000	150,000	666,000

Notes: This table presents estimates of annual childhood exposure effects for different outcome variables. Online Appendix E provides the precise sample and specification details. The estimates in the first row present the estimated effect of spending an additional year in a CZ where other children have one unit higher outcome ranks or probabilities. Columns 1 through 6 show the impact of an additional year in a CZ where children of the same race and gender have one unit higher outcome ranks or probabilities, separately for age ranges below 23 and above 23. Columns 7 through 12 add placebo forecasts of the outcomes of other races in addition to own-race forecasts. Note that all observation counts shown are rounded as described in the notes to Table I.

Appendix Table I
Theories of Racial Disparities

Explanation	Selected References
A. Family-Level Factors	
Parental Income	Magnuson & Duncan 2006; Rothstein & Wozny 2012
Parental Human Capital & Wealth	Oliver & Shapiro 1995; Orr 2003; Conley 2010
Family Structure and Stability	McAdoo 2002; Burchinal et al. 2011
Ability at Birth	Murray & Hernstein 1994; Rushton & Jensen 2005; Fryer & Levitt 2006
B. Structural Features of Environment	
Segregation, Neighborhoods	Wilson 1987; Massey & Denton 1993; Sampson and Wilson 1995; Smith 2005
School Quality	Smith & Welch 1989; Card & Krueger 1992; Jencks & Phillips 1998; Dobbie & Fryer 2011
Discrimination in the Labor Market	Donohue & Heckman 1992; Heckman 1998; Pager 2003; Bertrand & Mullainathan 2004
Discrimination in Criminal Justice	Steffensmeier, Ulmer, Kramer 1998; Eberhardt et al. 2004; Alexander 2010
Social Alienation, Stereotype Threat	Steele & Aaronson 1995; Tatum 2004; Glover, Pallais, Pariente 2017
C. Cultural Factors and Social Norms	
Identity and Oppositional Norms	Fordham & Ogbu 1986; Noguera 2003; Carter 2005; Austen-Smith & Fryer 2005
Aspirations or Role Models	Mickelson 1990; Small, Harding, & Lamont 2010

Notes: In this table, we organize theories of racial disparities into three broad categories and provide selected references to prior work discussing each of these theories.

Appendix Table II
Sample Sizes and Coverage Rates by Birth Cohort

A. Coverage Rates by Child's Birth Cohort

Cohort	2015 ACS: Born in U.S. or Arrived Before Age 16 (1,000s) (1)	Percent Matched to Parents with Positive Income (2)	And with Non- missing Race (3)	And at Least one Tract (4)	And Appear in ACS at Some Point between 2005-2015 (5)
1978	3,334	94.5%	88.6%	88.1%	12.3%
1979	3,594	92.9%	88.3%	87.8%	12.1%
1980	3,715	95.1%	90.9%	90.4%	12.2%
1981	3,580	105.7%	97.1%	96.6%	12.8%
1982	3,660	104.1%	98.5%	98.0%	12.7%
1983	3,678	104.9%	97.9%	97.4%	12.5%
Average: Cohorts 78-83	21,561	99.6%	93.6%	93.1%	12.4%

B. Coverage Rates by Race and Ethnicity

	Pooled (6)	White (7)	Black (8)	Asian (9)	Hispanic (10)	American Indian (11)
Count in 2015 ACS	21,560,000	13,890,000	2,927,000	678,000	3,341,000	151,000
Share of 2015 ACS Total in Analysis Sample	98.8%	97.1%	94.0%	101.0%	78.3%	109.3%

Notes: This table describes the coverage rates of our sample relative to the target population. Panel A presents statistics on coverage rates by birth cohort. Note that all observation counts shown are rounded as described in the notes to Table I. Column 1 presents estimates of the size of the target population (in 1,000's), based on the number of people who were born in the U.S. or who moved to the U.S. before age 16 in the 2015 American Community Survey. We use the ACS person weights to estimate total counts from the ACS sample. Column 2 shows the number of children in the tax data who are linked to parents with positive income, measured as a percentage relative to the totals in Column 1. Column 3 reports the number of children in our linked sample for whom we have information on race, again as a percentage of the counts in Column 1. In Column 4, we further require that children are assigned to at least one census tract prior to age 23. In Column 5, we report the fraction of the resulting children who we ever observe as ACS respondents. Panel B shows the coverage of each racial and ethnic group in our analysis sample relative to the counts of these groups in the 2015 ACS, pooling the 1978-83 birth cohorts. See Appendix B for further details.

Appendix Table III
Characteristics of Matched vs. Unmatched Children

		2015 ACS (1978- 83 cohorts, born in US or came before 16)	In 2015 ACS and appears in our analysis sample	In 2015 ACS but does not appear in our analysis sample
		(1)	(2)	(3)
<i>A. Individual Income Ranks in ACS Data by Race and Ethnicity</i>				
Pooled	Rank	49.99	52.10	42.01
White	Rank	53.02	54.19	46.27
	% of Sample	64.4%	69.4%	45.6%
Black	Rank	41.36	43.09	36.60
	% of Sample	13.6%	12.6%	17.2%
Asian	Rank	60.02	62.63	52.72
	% of Sample	3.1%	2.9%	3.9%
Hispanic	Rank	43.54	47.69	37.12
	% of Sample	15.5%	12.3%	30.3%
American Indian	Rank	37.29	37.46	36.97
	% of Sample	0.7%	0.6%	1.2%
"Other"	Rank	49.67	51.61	43.44
	% of Sample	2.7%	2.6%	3.1%
<i>B. Other Outcomes</i>				
Marriage Rate		51.9%	54.1%	43.5%
College Attendance Rate		67.5%	71.2%	53.6%
Incarceration Rate		1.9%	1.1%	4.7%

Notes: This table compares the characteristics of children who appear in our linked analysis sample vs. those who do not appear in the sample using data from the 2015 ACS. Panel A presents mean individual income ranks and sample shares by race. Panel B presents statistics on other outcomes measured in the ACS, pooling across races. In Column 1 we present statistics using the 2015 ACS, restricting to those who were born in the years 1978-1983, were born in the US, or moved to the U.S. before age 16. We estimate the total counts and individual income ranks using the ACS person weights in this column. The income ranks are calculated using ACS income and are computed by ranking children within their birth cohort. In Column 2, we restrict the sample in 1 to children in our analysis sample i.e. those whom we can match to parents with positive income and for whom we have race information. In Column 3 we present statistics on those who appear in Column 1 but not in Column 2, i.e. children excluded from our analysis sample but part of the target sample. See Section III for definitions of the outcome variables.

Appendix Table IV
Comparison of Tax Data Income Measures and Characteristics to CPS and ACS Data

	Analysis Sample in 2015 ACS				
	Publicly Available CPS 2012-2016 (1)	Publicly Available ACS 2012-2016 (2)	Characteristics in ACS (3)	Subsample with 0 Income in Tax Records: Chars. in ACS (5)	
				Incomes in Tax Records (4)	
<i>A. Income Statistics</i>					
% Zero Income	8.1%	10.4%	9.5%	10.1%	37.5%
% Negative Income	0.1%	0.1%	0.1%	2.1%	0.1%
Mean	42,550	43,760	42,890	44,990	12,240
Standard Deviation	56,180	52,630	51,200	117,700	27,500
p10	160	0	300	0	0
p25	14,000	12,170	13,400	11,150	0
p50	33,000	32,810	34,000	33,370	5,000
p75	55,200	57,700	57,010	58,440	13,970
p90	85,250	91,140	89,000	92,330	34,000
p99	200,580	255,000	210,000	250,400	100,000
<i>B. Demographic Statistics</i>					
% Married	55.6%	55.6%	54.0%	-	28.0%
% Female	50.8%	49.9%	50.3%	-	48.2%
% Live in South	37.8%	38.1%	37.8%	-	44.5%
% White	66.2%	64.9%	67.3%	-	58.2%
% Black	13.0%	13.5%	12.7%	-	19.3%
% Asian	3.9%	3.6%	3.5%	-	2.2%
% Hispanic	14.4%	15.1%	13.2%	-	15.9%
% American Indian	0.8%	0.8%	0.6%	-	1.2%
% Attend College	67.4%	61.0%	70.2%	-	41.9%

Notes: This table presents summary statistics on income distributions (Panel A) and demographics (Panel B) for five different samples. The first two columns use the (publicly available) 2012-2016 Current Population Survey (CPS) and 2012-2016 ACS, focusing on individuals in the 1978-83 birth cohorts who were born in the U.S. or came to the U.S. before age 16. Column 3 uses data from the 2015 ACS who appear in our analysis sample, and measures their incomes and other characteristics in the ACS data. Column 4 uses the same sample as Column 3, but reports income data from the tax records. Column 5 shows statistics on income and other characteristics using ACS data for individuals who appear in both the ACS and the analysis sample, but who have zero income in the tax data in 2015 (i.e., those who have no 1040 or W-2 forms in 2015).

Appendix Table V
Summary Statistics on Children's Outcomes by Race

Race	Pooled (1)	White (2)	Black (3)	Asian (4)	Hispanic (5)	American Indian (6)
Household Income						
Median (\$)	42,030	53,730	20,650	63,720	35,180	22,260
Mean (\$)	63,530	74,740	31,160	100,900	48,600	35,510
Mean Percentile Rank	50.00	55.65	34.76	60.65	45.65	36.73
Individual Income						
Median (\$)	29,210	33,620	19,550	43,690	27,140	16,610
Mean (\$)	40,700	45,340	27,450	63,620	34,590	25,780
Mean Percentile Rank	50.00	53.28	42.01	60.31	48.10	39.65
Employment						
Employed in Tax Data	85.3%	88.9%	80.7%	90.6%	84.9%	76.8%
Employed in ACS	84.7%	86.5%	74.9%	88.2%	81.5%	72.8%
Hours of Work per Week	31.82	32.96	25.99	34.12	29.72	24.38
Wage Rate						
Median (\$/hour)	18.11	18.79	14.67	23.94	16.19	13.76
Mean (\$/hour)	22.42	22.97	18.12	30.08	20.09	17.27
Mean Rank	50.00	51.32	40.98	61.17	45.48	38.83
Other Outcomes						
Marriage Rate	45.0%	54.7%	16.3%	50.0%	37.4%	30.9%
HS Dropout Rate	13.9%	11.4%	22.2%	8.6%	23.2%	23.2%
College Attendance Rate	63.6%	67.2%	50.1%	79.0%	50.5%	44.7%
Incarceration Rate	1.5%	0.9%	5.1%	0.3%	1.5%	2.9%
Sample Size	21,310,000	13,490,000	2,750,000	685,000	2,615,000	165,000
ACS Sample Size	4,169,000	2,986,000	456,000	131,000	464,000	40,000

Notes: This table presents summary statistics on children's incomes in adulthood and other outcomes by race using our primary analysis sample (children in the 1978-1983 birth cohorts). Column 1 shows statistics for all children we link to parents with positive income, including those with missing race information; this is the sample on which children are assigned income ranks. Columns 2-6 present statistics for children with non-missing race information, based on their race and ethnicity. See Section III.B for variable definitions and data sources. We report sample sizes both for variables measured in the full sample and those measured using 2005-2015 ACS data.

Appendix Table VI
Summary Statistics on Children's Outcomes by Race for those with Mothers Born in the US

Race	Pooled (1)	White (2)	Black (3)	Asian (4)	Hispanic (5)	American Indian (6)
Household Income						
Median (\$)	48,070	56,390	21,670	57,540	36,740	23,350
Mean (\$)	68,240	76,020	32,030	84,980	53,520	36,240
Mean Percentile Rank	52.99	56.91	35.45	58.11	46.91	37.45
Individual Income						
Median (\$)	31,670	34,710	20,540	38,760	27,450	17,520
Mean (\$)	42,570	45,790	28,140	52,460	37,170	26,170
Mean Percentile Rank	51.81	54.10	42.77	57.40	48.49	40.30
Employment						
Employed in Tax Data	87.9%	90.0%	81.7%	90.5%	85.7%	78.0%
Employed in ACS	83.8%	85.5%	73.9%	85.0%	79.0%	71.7%
Hours of Work per Week	30.93	32.00	24.74	31.39	27.84	23.33
Wage Rate						
Median (\$/hour)	17.18	17.67	13.95	19.63	15.42	13.56
Mean (\$/hour)	21.05	21.56	17.37	24.78	19.16	16.86
Mean Rank	47.68	48.87	39.31	53.62	43.54	38.01
Other Outcomes						
Marriage Rate	50.3%	57.0%	17.2%	48.4%	39.3%	32.2%
HS Dropout Rate	15.8%	14.2%	23.7%	14.5%	22.0%	24.0%
College Attendance Rate	61.4%	64.2%	48.2%	68.9%	50.9%	42.9%
Incarceration Rate	1.2%	0.7%	4.6%	0.4%	1.5%	2.6%
Sample Size	4,783,000	3,716,000	499,000	28,500	270,000	47,000
ACS Sample Size	1,699,000	1,364,000	177,000	10,500	97,500	19,500

Notes: This table presents statistics that are analagous to those in Appendix Table V, but restricting to children whose mothers were born in the United States. We measure mother's place of birth in the ACS or 2000 Long Form. The sample sizes are smaller than those in Appendix Table V because we limit the sample to children whose mothers appear in the ACS or Long Form and also were born in the United States. See notes to Appendix Table V for further details.

Appendix Table VII
Summary Statistics on Children's Outcomes by Race and Gender

	Pooled		White		Black		Asian		Hispanic		American Indian	
	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Household Income												
Median (\$)	40,960	43,200	51,960	55,740	17,730	22,690	56,580	71,880	35,280	35,080	20,890	23,450
Mean (\$)	60,490	66,700	71,610	78,000	29,270	32,980	89,990	112,300	46,310	50,900	34,140	36,920
Mean Percentile Rank	48.67	51.39	54.54	56.80	32.60	36.83	57.50	63.94	44.64	46.66	35.69	37.82
Individual Income												
Median (\$)	34,910	24,170	40,710	26,580	18,220	20,400	45,550	41,730	32,250	22,930	19,030	14,870
Mean (\$)	46,970	34,170	53,700	36,610	27,650	27,260	68,230	58,820	39,410	29,750	29,140	22,300
Mean Percentile Rank	53.66	46.18	58.43	47.90	40.85	43.12	61.52	59.04	51.66	44.52	41.98	37.25
Employment												
Employed in Tax Data	83.7%	87.0%	88.4%	89.3%	74.1%	87.0%	89.2%	92.0%	83.2%	86.6%	74.7%	79.0%
Employed in ACS	88.5%	80.9%	91.5%	81.5%	70.0%	79.4%	90.5%	85.8%	85.5%	77.7%	75.7%	69.9%
Hours of Work per Week	35.71	28.02	37.66	28.29	24.87	27.01	36.31	31.92	33.05	26.56	26.25	22.51
Wage Rate												
Median (\$/hour)	19.18	17.18	19.63	17.67	14.72	14.46	23.53	24.38	16.84	15.69	14.46	13.12
Mean (\$/hour)	23.48	21.29	24.13	21.68	18.32	17.96	30.12	30.04	20.79	19.36	18.00	16.48
Mean Rank	52.10	47.76	53.63	48.75	41.35	40.69	60.63	61.74	46.97	43.93	40.65	36.88
Other Outcomes												
Marriage Rate	42.5%	47.7%	51.5%	58.1%	16.8%	15.8%	45.4%	54.7%	35.1%	39.7%	29.0%	32.9%
HS Dropout Rate	16.4%	11.5%	13.4%	9.3%	27.2%	17.6%	10.0%	7.2%	26.7%	19.8%	26.2%	20.2%
College Attendance Rate	57.8%	69.3%	61.6%	72.8%	41.5%	57.9%	75.7%	82.5%	44.5%	56.3%	38.1%	51.5%
Incarceration Rate	2.7%	0.3%	1.6%	0.2%	10.3%	0.6%	0.5%	0.0%	2.9%	0.2%	5.1%	0.8%
Sample Size	10,870,000	10,430,000	6,891,000	6,599,000	1,348,000	1,402,000	350,000	335,000	1,312,000	1,303,000	84,000	81,500
ACS Sample Size	2,075,000	2,095,000	1,495,000	1,490,000	218,000	238,000	66,000	64,500	230,000	234,000	20,000	20,000

Notes: This table presents statistics analogous to those in Appendix Table VI, but presents results separately for each gender within each race. For more detail on the analysis, see the notes to Appendix Table VI.

Appendix Table VIII
Summary Statistics on Parents' Incomes and Characteristics by Race

	Pooled (1)	White (2)	Black (3)	Asian (4)	Hispanic (5)	American Indian (6)
Household Income						
25th percentile (\$)	27,010	39,830	16,070	23,650	17,920	17,940
Median (\$)	55,810	70,640	29,200	53,010	33,060	34,850
75th percentile (\$)	94,260	107,900	52,890	99,660	60,260	62,890
99th percentile (\$)	466,300	566,500	168,900	533,500	213,300	190,500
Mean (\$)	79,550	96,680	40,590	82,670	47,240	46,990
Mean Percentile Rank	50.00	57.86	32.72	49.20	36.17	36.76
Family Structure						
Two Parent	68.34%	79.35%	32.16%	80.44%	57.03%	57.94%
Father Present	78.86%	86.09%	49.54%	88.41%	73.82%	70.17%
Mother Present	89.48%	93.26%	82.62%	92.02%	83.21%	87.76%
Education						
Mom HS Dropout	12.32%	7.38%	17.07%	21.90%	37.44%	18.22%
Dad HS Dropout	13.65%	8.90%	20.18%	17.09%	41.38%	20.94%
Mom College	55.75%	59.35%	50.66%	59.15%	36.04%	49.29%
Dad College	56.92%	60.55%	46.73%	66.38%	35.75%	43.59%
Wealth						
Home Ownership Rate	75.58%	81.59%	56.79%	70.62%	62.41%	67.66%
Median Monthly Mortgage Payment (\$)	502	570	0	827	289	0
Mean Monthly Mortgage Payment (\$)	704	742	490	1067	633	319
Median Number of Cars	2	2	2	2	2	2
Mean Number of Cars	2.30	2.44	1.73	2.39	2.14	2.01
Place of Birth						
Foreign Born Mother	12.26%	4.41%	8.37%	81.76%	49.07%	3.80%
Foreign Born Father	12.85%	4.29%	10.82%	79.96%	54.08%	4.22%
Tract-Level Characteristics						
Mean Parent Income Rank	51.62	56.70	38.96	53.39	41.46	44.39
Single Parent Share (2000)	30.20%	23.06%	53.84%	29.23%	38.85%	32.17%
Own-Race Single Parent Share (2000)	30.12%	19.09%	66.70%	18.71%	41.05%	38.97%
Share White (2000)	66.84%	81.87%	32.78%	50.78%	37.21%	55.90%
Sample Size	21,310,000	13,490,000	2,750,000	685,000	2,615,000	165,000
ACS Sample Size	5,451,000	3,887,000	544,000	157,000	530,000	49,000

Notes: This table presents statistics on the characteristics of the parents of the children in our analysis sample (1978-83 birth cohorts). See Section III.B for variable definitions and data sources. Statistics on mother's and father's education and place of birth are reported only for the subset of children for whom the mother or father is present. Tract characteristics are calculated based on the first non-missing parental tract. Poverty rate and the share white are calculated using publicly available Census 2000 data at the tract level (see Online Appendix C). All other tract-level characteristics are calculated in the Census microdata. We report sample sizes both for variables measured in the full sample and those measured using 2005-2015 ACS data.

Appendix Table IX
Relative Mobility by Race and Birth Cohort

Child Birth Cohort	White (1)	Black (2)	Asian (3)	Hispanic (4)	American Indian (5)
1978	0.322	0.254	0.198	0.249	0.289
1979	0.326	0.256	0.193	0.250	0.280
1980	0.327	0.255	0.189	0.247	0.291
1981	0.328	0.259	0.187	0.244	0.307
1982	0.328	0.254	0.180	0.240	0.303
1983	0.329	0.252	0.174	0.240	0.316

Notes: This table presents estimates of relative mobility (β_r) by race, separately for each birth cohort of children in our primary analysis sample. We estimate these slopes using OLS regressions of children's household income ranks on their parents' household income ranks, separately by cohort-race cell, and report the coefficient on parent rank in each regression.

Appendix Table X
Correlations between Individual Income of Black and White Males and Neighborhood Covariates by Parent Income

Covariate	Parents at 25th Percentile of National Distribution			Parents at 75th Percentile of National Distribution		
	White Male	Black Male	White - Black	White Male	Black Male	White - Black
A. Measures of "Good" Neighborhoods						
Economy						
Share in Poverty (2000)	-0.446 (0.004)	-0.375 (0.006)	-0.138 (0.006)	-0.313 (0.004)	-0.252 (0.006)	0.048 (0.006)
Mean Household Income (2000)	0.522 (0.004)	0.391 (0.006)	0.216 (0.006)	0.425 (0.004)	0.266 (0.006)	0.001 (0.006)
Employment Rate	0.145 (0.005)	0.219 (0.007)	0.029 (0.007)	0.119 (0.005)	0.122 (0.007)	-0.053 (0.007)
Share Working in Manufacturing (2010)	-0.170 (0.004)	-0.083 (0.006)	-0.115 (0.006)	-0.076 (0.004)	-0.055 (0.006)	-0.017 (0.006)
Family Structure						
Share Single Parents (2000)	-0.502 (0.004)	-0.400 (0.006)	-0.145 (0.006)	-0.436 (0.004)	-0.270 (0.006)	0.057 (0.006)
Share Married (2000)	0.304 (0.004)	0.368 (0.006)	0.044 (0.006)	0.242 (0.004)	0.251 (0.006)	-0.088 (0.006)
School						
3rd Grade Math Score (2013)	0.259 (0.004)	0.193 (0.006)	-0.009 (0.006)	0.299 (0.004)	0.178 (0.006)	-0.063 (0.006)
8th Grade Math Score (2013)	0.346 (0.004)	0.184 (0.006)	0.082 (0.007)	0.340 (0.004)	0.171 (0.006)	-0.026 (0.007)
HS Suspension Rate (2013)	-0.227 (0.004)	-0.078 (0.006)	-0.133 (0.007)	-0.170 (0.004)	-0.071 (0.006)	-0.001 (0.007)
Average ELA Score (2013)	0.290 (0.004)	0.213 (0.006)	0.014 (0.006)	0.327 (0.004)	0.178 (0.006)	-0.049 (0.006)
Educational Attainment						
Share Less Than HS Educated (2000)	-0.506 (0.004)	-0.332 (0.006)	-0.195 (0.006)	-0.347 (0.004)	-0.249 (0.006)	0.017 (0.006)
Share College Educated (2000)	0.482 (0.004)	0.315 (0.006)	0.238 (0.006)	0.371 (0.004)	0.251 (0.006)	0.012 (0.006)
Housing						
Share who Own Home (2010)	0.301 (0.004)	0.271 (0.006)	0.049 (0.006)	0.285 (0.004)	0.212 (0.006)	-0.064 (0.006)
Median 2 Bedroom Rent (2015)	0.353 (0.004)	0.246 (0.006)	0.198 (0.007)	0.236 (0.004)	0.114 (0.007)	0.039 (0.007)
Healthcare Access						
Share Adults Insured (2008-2012)	0.407 (0.004)	0.188 (0.006)	0.133 (0.006)	0.439 (0.004)	0.216 (0.006)	-0.016 (0.006)
B. Race-Specific Measures						
Economy						
Share Black in Poverty (2000)	-0.199 (0.005)	-0.321 (0.006)	-0.032 (0.006)	-0.106 (0.005)	-0.175 (0.006)	0.033 (0.006)
Share White in Poverty (2000)	-0.428 (0.004)	-0.202 (0.006)	-0.138 (0.006)	-0.304 (0.004)	-0.167 (0.006)	0.029 (0.006)
Family Structure						
Black Father Presence (p25)	0.032 (0.005)	0.193 (0.006)	-0.096 (0.006)	0.018 (0.005)	0.121 (0.006)	-0.078 (0.006)
White Father Presence (p25)	0.119 (0.004)	0.133 (0.006)	-0.064 (0.006)	0.152 (0.004)	0.084 (0.006)	-0.030 (0.006)
Black Mother Presence (p25)	-0.017 (0.005)	-0.031 (0.006)	-0.023 (0.006)	-0.035 (0.005)	-0.003 (0.006)	-0.022 (0.006)
White Mother Presence (p25)	0.132 (0.004)	0.081 (0.006)	0.067 (0.006)	0.084 (0.004)	0.063 (0.006)	-0.024 (0.006)
Housing						
Median Home Value Black (2000)	0.362 (0.004)	0.266 (0.006)	0.184 (0.006)	0.269 (0.005)	0.145 (0.006)	0.027 (0.007)
Median Home Value White (2000)	0.413 (0.004)	0.203 (0.006)	0.213 (0.006)	0.313 (0.004)	0.139 (0.006)	0.038 (0.006)
Racial Bias						
IAT Score for Black	0.074 (0.021)	0.062 (0.027)	0.120 (0.027)	0.078 (0.021)	-0.060 (0.027)	0.101 (0.027)
IAT Score for White	-0.105 (0.018)	-0.038 (0.027)	-0.164 (0.026)	-0.004 (0.018)	0.079 (0.027)	-0.149 (0.026)
IAT Score White - Black	-0.100 (0.021)	-0.073 (0.027)	-0.193 (0.026)	-0.075 (0.021)	0.094 (0.027)	-0.169 (0.026)
Interracial Marriage Attitudes	-0.612 (0.121)	-0.050 (0.154)	-0.673 (0.114)	-0.396 (0.140)	0.271 (0.149)	-0.643 (0.118)
Racial Animus Index	-0.352 (0.067)	-0.229 (0.074)	-0.105 (0.075)	-0.114 (0.072)	-0.102 (0.075)	-0.01 (0.076)
Healthcare Access						
Share Adults Insured Black (2008-2012)	0.123 (0.004)	0.143 (0.006)	0.060 (0.006)	0.109 (0.004)	0.135 (0.006)	-0.018 (0.006)
Share Adults Insured White (2008-2012)	0.442 (0.004)	0.131 (0.006)	0.179 (0.006)	0.456 (0.004)	0.129 (0.006)	0.014 (0.006)
C. Other						
Population Density (2000)	0.073 (0.004)	0.079 (0.006)	0.097 (0.006)	0.049 (0.004)	-0.064 (0.006)	0.074 (0.006)
Share Black (2010)	-0.265 (0.004)	-0.121 (0.006)	-0.216 (0.006)	-0.222 (0.004)	-0.120 (0.006)	0.016 (0.006)
Share of Population Younger than 18 (2000)	-0.002 (0.004)	-0.171 (0.006)	-0.091 (0.006)	0.043 (0.004)	-0.111 (0.006)	-0.021 (0.006)
Share Foreign Born (2000)	0.134 (0.004)	0.182 (0.006)	0.134 (0.006)	0.057 (0.004)	-0.016 (0.006)	0.064 (0.006)
Share Divorced (2000)	-0.450 (0.004)	-0.236 (0.006)	-0.089 (0.006)	-0.464 (0.004)	-0.174 (0.006)	0.014 (0.006)

Notes: This table presents a set of correlations between individual outcomes of black and white males and various neighborhood characteristics measured at tract-level. See section III for details on variable definitions. The variables are measured at the tract level aside from the racial bias measures which are at the county, state, and media market level. For all tract level covariates, we present signal correlations, which we calculate by dividing the correlation by the square root of the ratio of signal variance to total variance. For non-tract level covariates (e.g. racial bias), we present raw correlations. Standard errors are listed below each correlation in parentheses.

Appendix Table XI

Correlations between Individual Income of Black and White Males and Neighborhood Covariates by Parent Income, Among Low Poverty Areas

Covariate	Parents at 25th Percentile of National Distribution			Parents at 75th Percentile of National Distribution		
	White Male	Black Male	White - Black	White Male	Black Male	White - Black
A. Measures of "Good" Neighborhoods						
Economy						
Share in Poverty (2000)	-0.362 (0.005)	-0.216 (0.010)	-0.072 (0.010)	-0.324 (0.005)	-0.177 (0.010)	0.019 (0.010)
Mean Household Income (2000)	0.461 (0.005)	0.237 (0.010)	0.170 (0.010)	0.435 (0.005)	0.196 (0.010)	0.039 (0.010)
Employment Rate	0.026 (0.006)	0.008 (0.012)	-0.002 (0.012)	0.091 (0.006)	0.014 (0.012)	-0.022 (0.012)
Share Working in Manufacturing (2010)	-0.148 (0.005)	-0.172 (0.010)	-0.009 (0.010)	-0.066 (0.005)	-0.080 (0.010)	0.005 (0.010)
Family Structure						
Share Single Parents (2000)	-0.407 (0.005)	-0.156 (0.010)	-0.045 (0.010)	-0.439 (0.005)	-0.173 (0.010)	0.034 (0.010)
Share Married (2000)	0.123 (0.005)	0.090 (0.010)	-0.063 (0.010)	0.169 (0.005)	0.145 (0.010)	-0.084 (0.010)
School						
3rd Grade Math Score (2013)	0.219 (0.005)	0.087 (0.010)	-0.008 (0.010)	0.309 (0.005)	0.144 (0.010)	-0.049 (0.010)
8th Grade Math Score (2013)	0.300 (0.005)	0.104 (0.010)	0.072 (0.010)	0.352 (0.005)	0.141 (0.010)	-0.008 (0.010)
HS Suspension Rate (2013)	-0.188 (0.006)	-0.047 (0.010)	-0.099 (0.010)	-0.154 (0.006)	-0.082 (0.010)	0.016 (0.010)
Average ELA Score (2013)	0.246 (0.005)	0.120 (0.010)	0.010 (0.010)	0.344 (0.005)	0.145 (0.010)	-0.036 (0.010)
Educational Attainment						
Share Less Than HS Educated (2000)	-0.427 (0.005)	-0.173 (0.010)	-0.132 (0.010)	-0.312 (0.005)	-0.146 (0.010)	-0.008 (0.010)
Share College Educated (2000)	0.434 (0.005)	0.183 (0.010)	0.181 (0.010)	0.373 (0.005)	0.176 (0.010)	0.04 (0.010)
Housing						
Share who Own Home (2010)	0.166 (0.005)	0.039 (0.010)	0.025 (0.010)	0.239 (0.005)	0.094 (0.010)	-0.028 (0.010)
Median 2 Bedroom Rent (2015)	0.341 (0.006)	0.284 (0.011)	0.111 (0.011)	0.253 (0.006)	0.102 (0.011)	0.046 (0.011)
Healthcare Access						
Share Adults Insured (2008-2012)	0.368 (0.005)	0.104 (0.010)	0.110 (0.010)	0.465 (0.005)	0.178 (0.010)	-0.013 (0.010)
B. Race-Specific						
Economy						
Share White in Poverty (2000)	-0.314 (0.005)	-0.056 (0.010)	-0.117 (0.010)	-0.264 (0.005)	-0.074 (0.010)	-0.022 (0.010)
Share Black in Poverty (2000)	-0.075 (0.006)	-0.161 (0.010)	0.037 (0.010)	-0.051 (0.006)	-0.056 (0.010)	0.011 (0.010)
Family Structure						
Black Father Presence (p25)	-0.015 (0.008)	0.103 (0.010)	-0.134 (0.010)	-0.009 (0.008)	0.094 (0.010)	-0.087 (0.010)
White Father Presence (p25)	0.116 (0.005)	0.036 (0.010)	-0.082 (0.010)	0.151 (0.005)	0.041 (0.010)	-0.015 (0.010)
Black Mother Presence (p25)	-0.027 (0.008)	-0.003 (0.010)	-0.061 (0.010)	-0.040 (0.008)	-0.016 (0.010)	-0.019 (0.010)
White Mother Presence (p25)	0.102 (0.005)	0.045 (0.010)	-0.001 (0.010)	0.078 (0.005)	0.025 (0.010)	-0.021 (0.010)
Housing						
Median Home Value Black (2000)	0.323 (0.006)	0.175 (0.010)	0.133 (0.010)	0.270 (0.006)	0.120 (0.010)	0.035 (0.010)
Median Home Value White (2000)	0.379 (0.005)	0.140 (0.010)	0.165 (0.010)	0.327 (0.005)	0.118 (0.010)	0.054 (0.010)
Racial Bias						
IAT Score for Black	0.073 (0.039)	0.090 (0.054)	0.084 (0.054)	0.094 (0.039)	0.022 (0.054)	0.101 (0.054)
IAT Score for White	-0.092 (0.034)	-0.172 (0.054)	0.063 (0.054)	0.012 (0.034)	-0.134 (0.054)	0.071 (0.054)
IAT Score White - Black	-0.093 (0.039)	-0.181 (0.053)	-0.035 (0.054)	-0.084 (0.039)	-0.100 (0.054)	-0.045 (0.054)
Interracial Marriage Attitudes	-0.428 (0.251)	-0.329 (0.273)	0.214 (0.282)	-0.298 (0.265)	-0.472 (0.254)	0.353 (0.270)
Racial Animus Index	-0.718 (0.132)	-0.679 (0.144)	0.209 (0.192)	-0.469 (0.167)	-0.520 (0.167)	0.400 (0.180)
Healthcare Access						
Share Adults Insured Black (2008-2012)	0.088 (0.006)	0.125 (0.010)	0.013 (0.010)	0.093 (0.006)	0.113 (0.010)	-0.027 (0.010)
Share Adults Insured White (2008-2012)	0.410 (0.005)	0.116 (0.010)	0.130 (0.010)	0.486 (0.005)	0.130 (0.010)	0.019 (0.010)
C. Other Variables						
Population Density (2000)	0.169 (0.005)	0.131 (0.010)	0.106 (0.010)	0.095 (0.005)	-0.022 (0.010)	0.076 (0.010)
Share Black (2010)	-0.169 (0.005)	0.044 (0.010)	-0.151 (0.010)	-0.211 (0.005)	-0.107 (0.010)	0.065 (0.010)
Share of Population Younger than 18 (2000)	0.105 (0.005)	0.073 (0.010)	-0.096 (0.010)	0.073 (0.005)	0.023 (0.010)	-0.051 (0.010)
Share Foreign Born (2000)	0.239 (0.005)	0.236 (0.010)	0.099 (0.010)	0.141 (0.005)	0.032 (0.010)	0.067 (0.010)
Share Divorced (2000)	-0.392 (0.005)	-0.186 (0.010)	-0.027 (0.010)	-0.473 (0.005)	-0.187 (0.010)	0.020 (0.010)

Notes: This table presents analogous statistics to those presented in Table II, but restricts the sample to places with fewer than 10% of residents below the federal poverty line, as measured by the 2000 Census. For variables that are not constructed at the tract level (racial bias), we restrict to counties, states, or media markets with fewer than 10% of residents in poverty by aggregating up tract level shares using population weights.

Appendix Table XII
Correlations between Individual Income of Black and White Females and Neighborhood Covariates by Parent Income

Covariate	Parents at 25th Percentile of National Distribution			Parents at 75th Percentile of National Distribution		
	White Female	Black Female	White - Black	White Female	Black Female	White - Black
<i>A. Measures of "Good" Neighborhoods</i>						
Economy						
Share in Poverty (2000)	-0.427 (0.004)	-0.377 (0.006)	-0.101 (0.006)	-0.321 (0.004)	-0.263 (0.006)	0.070 (0.006)
Mean Household Income (2000)	0.581 (0.003)	0.474 (0.005)	0.196 (0.006)	0.493 (0.004)	0.360 (0.006)	-0.051 (0.006)
Employment Rate	0.060 (0.005)	0.130 (0.007)	0.074 (0.007)	0.041 (0.005)	0.081 (0.007)	0.007 (0.007)
Share Working in Manufacturing (2010)	-0.242 (0.004)	-0.270 (0.006)	-0.089 (0.006)	-0.172 (0.004)	-0.210 (0.006)	0.059 (0.006)
Family Structure						
Share Single Parents (2000)	-0.326 (0.004)	-0.207 (0.006)	-0.116 (0.006)	-0.286 (0.004)	-0.218 (0.006)	0.070 (0.006)
Share Married (2000)	0.097 (0.004)	0.134 (0.006)	-0.004 (0.006)	0.063 (0.004)	0.158 (0.006)	-0.095 (0.006)
School						
3rd Grade Math Score (2013)	0.236 (0.004)	0.141 (0.006)	0.056 (0.006)	0.294 (0.004)	0.178 (0.006)	-0.051 (0.006)
8th Grade Math Score (2013)	0.324 (0.004)	0.170 (0.006)	0.110 (0.007)	0.333 (0.004)	0.185 (0.006)	-0.053 (0.007)
HS Suspension Rate (2013)	-0.189 (0.004)	-0.079 (0.006)	-0.129 (0.007)	-0.132 (0.004)	-0.069 (0.006)	-0.009 (0.007)
Average ELA Score (2013)	0.297 (0.004)	0.160 (0.006)	0.083 (0.006)	0.361 (0.004)	0.189 (0.006)	-0.042 (0.006)
Educational Attainment						
Share Less Than HS Educated (2000)	-0.510 (0.004)	-0.351 (0.006)	-0.155 (0.006)	-0.382 (0.004)	-0.269 (0.006)	0.053 (0.006)
Share College Educated (2000)	0.608 (0.003)	0.369 (0.006)	0.292 (0.006)	0.527 (0.003)	0.341 (0.006)	-0.004 (0.006)
Housing						
Share who Own Home (2010)	0.149 (0.004)	0.108 (0.006)	-0.016 (0.006)	0.168 (0.004)	0.164 (0.006)	-0.060 (0.006)
Median 2 Bedroom Rent (2015)	0.551 (0.004)	0.533 (0.006)	0.206 (0.007)	0.436 (0.004)	0.302 (0.006)	-0.006 (0.007)
Healthcare Access						
Share Adults Insured (2008-2012)	0.388 (0.004)	0.238 (0.006)	0.081 (0.006)	0.475 (0.004)	0.230 (0.006)	0.008 (0.006)
<i>B. Race-Specific Measures</i>						
Economy						
Share Black in Poverty (2000)	-0.222 (0.004)	-0.449 (0.006)	0.005 (0.006)	-0.143 (0.005)	-0.274 (0.006)	0.102 (0.006)
Share White in Poverty (2000)	-0.422 (0.004)	-0.128 (0.006)	-0.118 (0.006)	-0.352 (0.004)	-0.141 (0.006)	0.027 (0.006)
Family Structure						
Black Father Presence (p25)	-0.121 (0.005)	-0.190 (0.006)	-0.037 (0.006)	-0.072 (0.005)	-0.023 (0.006)	-0.024 (0.006)
White Father Presence (p25)	-0.129 (0.004)	-0.134 (0.006)	-0.105 (0.006)	-0.110 (0.004)	-0.007 (0.006)	-0.020 (0.006)
Black Mother Presence (p25)	0.028 (0.005)	0.126 (0.006)	-0.064 (0.006)	-0.015 (0.005)	0.025 (0.006)	-0.058 (0.006)
White Mother Presence (p25)	0.020 (0.004)	-0.010 (0.006)	0.026 (0.006)	-0.030 (0.004)	0.003 (0.006)	-0.026 (0.006)
Housing						
Median Home Value Black (2000)	0.456 (0.004)	0.481 (0.006)	0.186 (0.006)	0.350 (0.004)	0.320 (0.006)	-0.031 (0.007)
Median Home Value White (2000)	0.540 (0.003)	0.345 (0.006)	0.254 (0.006)	0.433 (0.004)	0.260 (0.006)	0.026 (0.006)
Racial Bias						
IAT Score for Black	0.061 (0.021)	0.223 (0.026)	0.174 (0.026)	0.060 (0.021)	0.101 (0.027)	0.119 (0.027)
IAT Score for White	-0.055 (0.018)	-0.283 (0.026)	-0.161 (0.026)	0.062 (0.018)	-0.203 (0.026)	-0.054 (0.027)
IAT Score White - Black	-0.074 (0.021)	-0.346 (0.025)	-0.235 (0.026)	-0.038 (0.021)	-0.202 (0.026)	-0.127 (0.027)
Interracial Marriage Attitudes	-0.604 (0.122)	-0.584 (0.125)	-0.577 (0.126)	-0.306 (0.145)	-0.366 (0.144)	-0.480 (0.135)
Racial Animus Index	-0.206 (0.070)	-0.373 (0.071)	-0.062 (0.076)	0.075 (0.072)	-0.367 (0.071)	0.181 (0.075)
Healthcare Access						
Share Adults Insured Black (2008-2012)	0.126 (0.004)	0.241 (0.006)	0.008 (0.006)	0.133 (0.004)	0.175 (0.006)	-0.031 (0.006)
Share Adults Insured White (2008-2012)	0.450 (0.004)	0.168 (0.006)	0.162 (0.006)	0.502 (0.004)	0.161 (0.006)	0.024 (0.006)
<i>C. Other</i>						
Population Density (2000)	0.231 (0.004)	0.301 (0.006)	0.158 (0.006)	0.160 (0.004)	0.070 (0.006)	0.065 (0.006)
Share Black (2010)	-0.185 (0.004)	-0.008 (0.006)	-0.242 (0.006)	-0.135 (0.004)	-0.047 (0.006)	-0.039 (0.006)
Share of Population Younger than 18 (2000)	-0.189 (0.004)	-0.119 (0.006)	-0.195 (0.006)	-0.263 (0.004)	-0.111 (0.006)	-0.120 (0.006)
Share Foreign Born (2000)	0.337 (0.004)	0.383 (0.006)	0.198 (0.006)	0.215 (0.004)	0.171 (0.006)	0.013 (0.006)
Share Divorced (2000)	-0.314 (0.004)	-0.187 (0.006)	-0.087 (0.006)	-0.326 (0.004)	-0.213 (0.006)	0.020 (0.006)

Notes: This table presents statistics analogous to the specifications in Appendix Table X, but correlating outcomes of females as opposed to males.

Appendix Table XIII
Summary Statistics for CZ Movers Analysis Samples

Sample:		1-time Movers		Non 1-time Movers (0 & 2+ Movers)	
		Black Males (1)	White Males (2)	Black Males (3)	White Males (4)
Parent Family Income (\$)	Mean	40,040	101,400	37,000	93,050
	Median	27,540	68,470	26,400	66,950
	Std. Dev.	97,670	301,400	55,560	257,300
	Num. of Obs.	305,000	1,600,000	3,145,000	14,110,000
Child Individual Income at 24 (\$)	Mean	13,360	18,810	12,030	19,150
	Median	6,699	13,360	4,990	13,760
	Std. Dev.	89,010	62,460	331,500	83,890
	Num. of Obs.	305,000	1,600,000	3,145,000	14,110,000
Child Individual Income at 30 (\$)	Mean	24,870	41,240	23,130	41,690
	Median	15,310	32,850	13,930	34,450
	Std. Dev.	140,100	153,100	111,900	188,400
	Num. of Obs.	150,000	884,000	1,623,000	7,887,000
Child Incarcerated in 2010	Mean	0.10	0.02	0.09	0.01
	Median	0	0	0	0
	Std. Dev.	0.30	0.13	0.28	0.12
	Num. of Obs.	123,000	712,000	2,415,000	11,940,000
Child Married at 30	Mean	0.16	0.42	0.13	0.43
	Median	0	0	0	0
	Std. Dev.	0.36	0.49	0.34	0.49
	Num. of Obs.	150,000	884,000	1,623,000	7,887,000

Notes: This table presents summary statistics for the samples used in our analyses of CZ-level exposure effects. The full analysis sample extends the core sample described in Section III by including additional cohorts up until 1991 in order to observe moves at younger ages. Columns 1 and 2 report summary statistics for black and white males whose parents moved across CZs exactly once throughout our sample window (1989-2015), are observed in their destination for at least two years, and moved at least 100 miles (based on their ZIP codes). We require estimates of origin and destination quality to be based on at least 25 individuals. Columns 3 and 4 report summary statistics for black and white males whose parents do not move across CZs throughout our sample window and for black and white males whose parents move more than once across CZs. Parent family income is the average pre-tax household income from 1994-2000 measured as AGI. Child individual income is defined as the sum of individual W-2 wage earnings and half of household self-employment income. Incarceration is based on the individual's group home status in the 2010 US population census. Marital status is defined based on the marital status listed on 1040 forms for tax filers; non-filers are coded as single. All dollar values are reported in 2015 dollars, deflated using the CPI-U. See Section III for further details on variable and sample definitions.

Appendix Table XIV
Childhood Exposure Effects for Females

<i>Outcome:</i>	Exposure Effects Using Baseline Specification						Exposure Effects Using Other Race Placebos					
	Individual Income at 30		Incarcerated in 2010		Married at Age 30		Individual Income at 30		Incarcerated in 2010		Married at Age 30	
<i>Sample:</i>	Black Females	White Females	Black Females	White Females	Black Females	White Females	Black Females	White Females	Black Females	White Females	Black Females	White Females
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Own-Race Exposure Effect:	-0.009 (0.003)	-0.009 (0.001)	-0.019 (0.006)	-0.008 (0.004)	-0.019 (0.004)	-0.023 (0.002)	-0.006 (0.005)	-0.011 (0.002)	-0.018 (0.006)	-0.008 (0.006)	-0.015 (0.004)	-0.024 (0.002)
<i>Placebos:</i>												
Under-23 Other-Race Placebo							-0.002 (0.003)	0.003 (0.002)	-0.011 (0.012)	0.000 (0.002)	-0.018 (0.004)	-0.002 (0.002)
Over-23 Own-Race Placebo	0.033 (0.022)	0.007 (0.010)	-0.025 (0.039)	-0.034 (0.030)	-0.014 (0.029)	-0.016 (0.011)	0.070 (0.031)	0.001 (0.013)	-0.040 (0.041)	0.025 (0.048)	-0.011 (0.029)	-0.008 (0.016)
Over-23 Other-Race Placebo							-0.040 (0.023)	0.020 (0.011)	0.109 (0.087)	0.001 (0.011)	-0.019 (0.024)	-0.021 (0.011)
Num. of Obs.	153,000	842,000	131,000	677,000	153,000	842,000	153,000	634,000	129,000	375,000	153,000	632,000

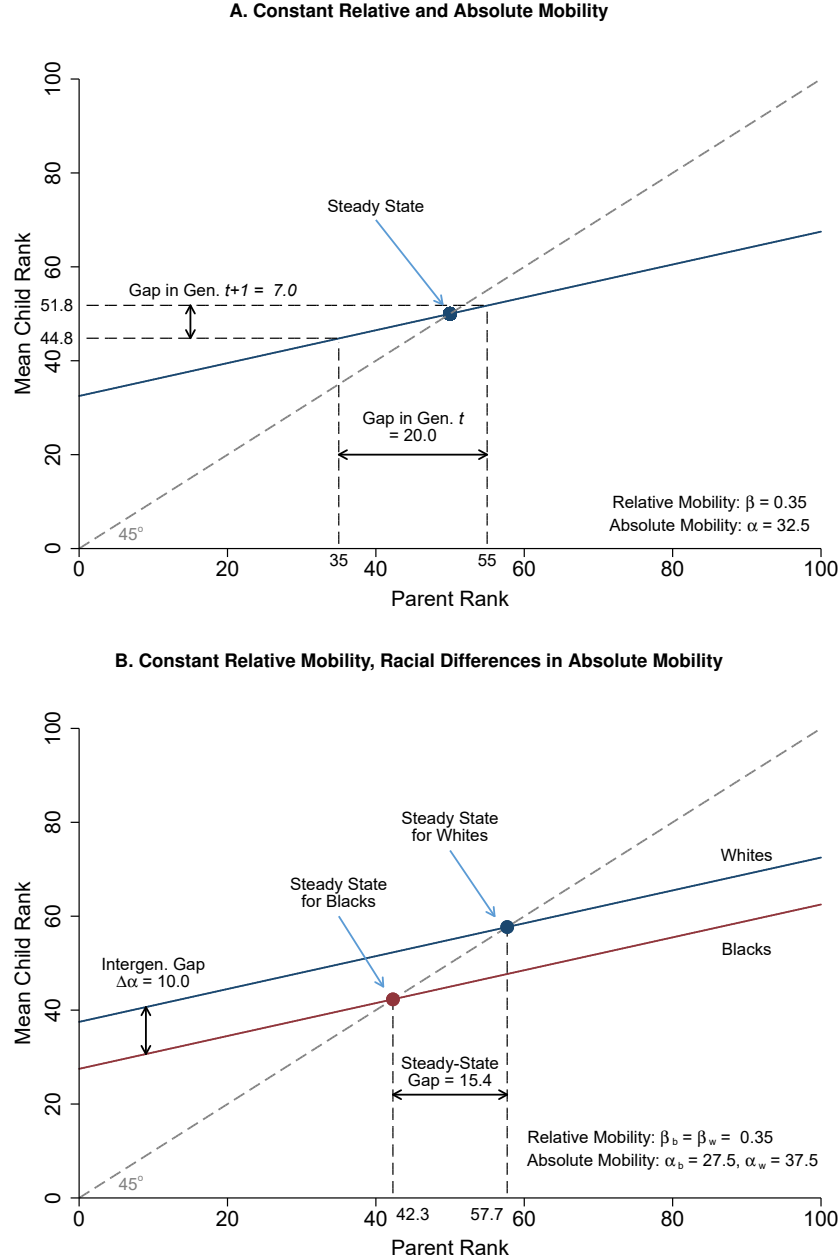
Notes: This table presents exposure effects analogous to those reported in Table IV, but for female children in our analysis sample. For more detail on the analysis, see the notes to Table IV.

Appendix Table XV
Neighborhoods With Good Outcomes for Black Males by Parent Income

	Parents at p=25		Parents at p=75	
	CZ Name	Neighborhood Name	CZ Name	Neighborhood Name
<i>A. Best Places</i>				
	Washington DC	Downtown Silver Spring, Woodside Park, Woodside Forest	Baton Rouge	East Baton Rouge, East Baton Rouge County
	Washington DC	College Park, Prince Georges' County	New Orleans	Terrytown, Jefferson County
	Washington DC	New Carrollton, Prince Georges' County	New Orleans	Woodmere, Jefferson County
	Washington DC	Greenbelt, Prince Georges' County	Newport News	Richneck, Newport News County
	New York	Queens Village, Queens		
	New York	Laurelton, Queens		
	New York	Wakefield / Eastchester, Bronx		
<i>B. Average Places</i>				
	Houston	Ost-South Union, Harris County	Memphis	Hickory Ridge-South Riverdale, Shelby County
	Houston	Sunnyside, Harris County	Chicago	Harvey, Cook County
	Memphis	White Haven, Shelby County	Chicago	South Holland, Cook County
	Memphis	Coro Lake, Shelby County		
<i>C. Worst Places</i>				
	Chicago	Robert Taylor Homes/Fuller Park, Cook County	Detroit	Harper Woods, Wayne County
	Chicago	Bronzeville, Cook County	Detroit	Hamtramck, Wayne County
	Chicago	Garfield Park, Cook County	Chicago	Humboldt Park, Cook County
	Chicago	Englewood	Chicago	West Garfield Park, Cook County
	Detroit	Chandler Park, Wayne County		
	Cincinnati	South Fairmont, Hamilton County		
	Los Angeles	South Los Angeles/Watts, Los Angeles County		

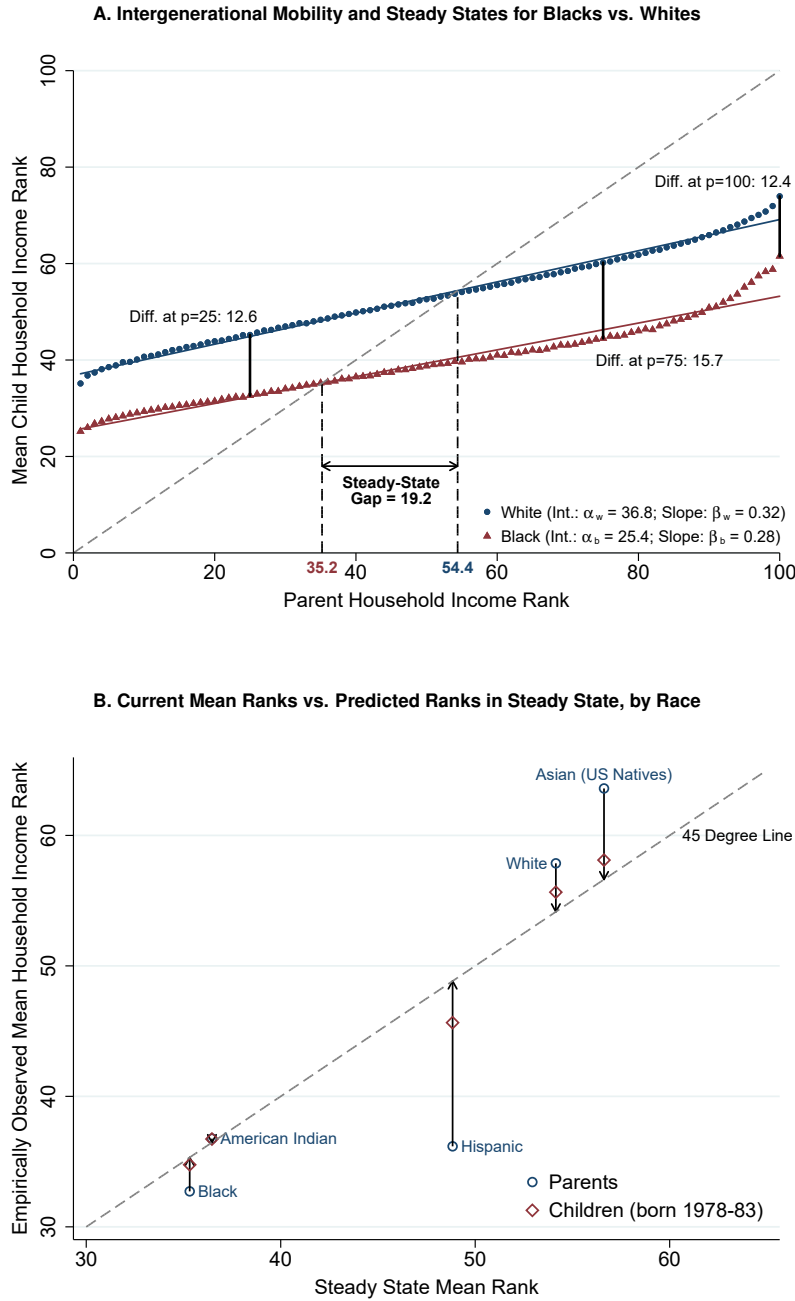
Notes: This table provides examples of good, average, and low outcome neighborhoods for black boys by parent income percentile. Neighborhoods are identified using percentile cutoffs in a tract-level dataset for individual income outcomes and father presence for black boys with parents at the 25th and 75th percentile of the national distribution of parent income. The "best" tracts are above the 95th percentile in outcomes for boys with parents at p25, and above the 90th percentile for boys with parents at p75. These tracts are below p75 in poverty share. They are also above the 75th percentile in terms of the number of black boys at that parent income with a father present, and there are at least 50 black boys in the tract below median income (p25) or above (p75). "Average" tracts are between p40 and p65 in individual income, father presence, and poverty rate. "Bad" tracts are those with outcomes in the 5th percentile, dad presence below the 75th percentile, and poor share above the 75th percentile. Neighborhoods names are assigned using a combination of the Zillow Neighborhood Name database as well as the maps provided by the American FactFinder tool.

FIGURE I: Intergenerational Mobility and the Evolution of Racial Disparities



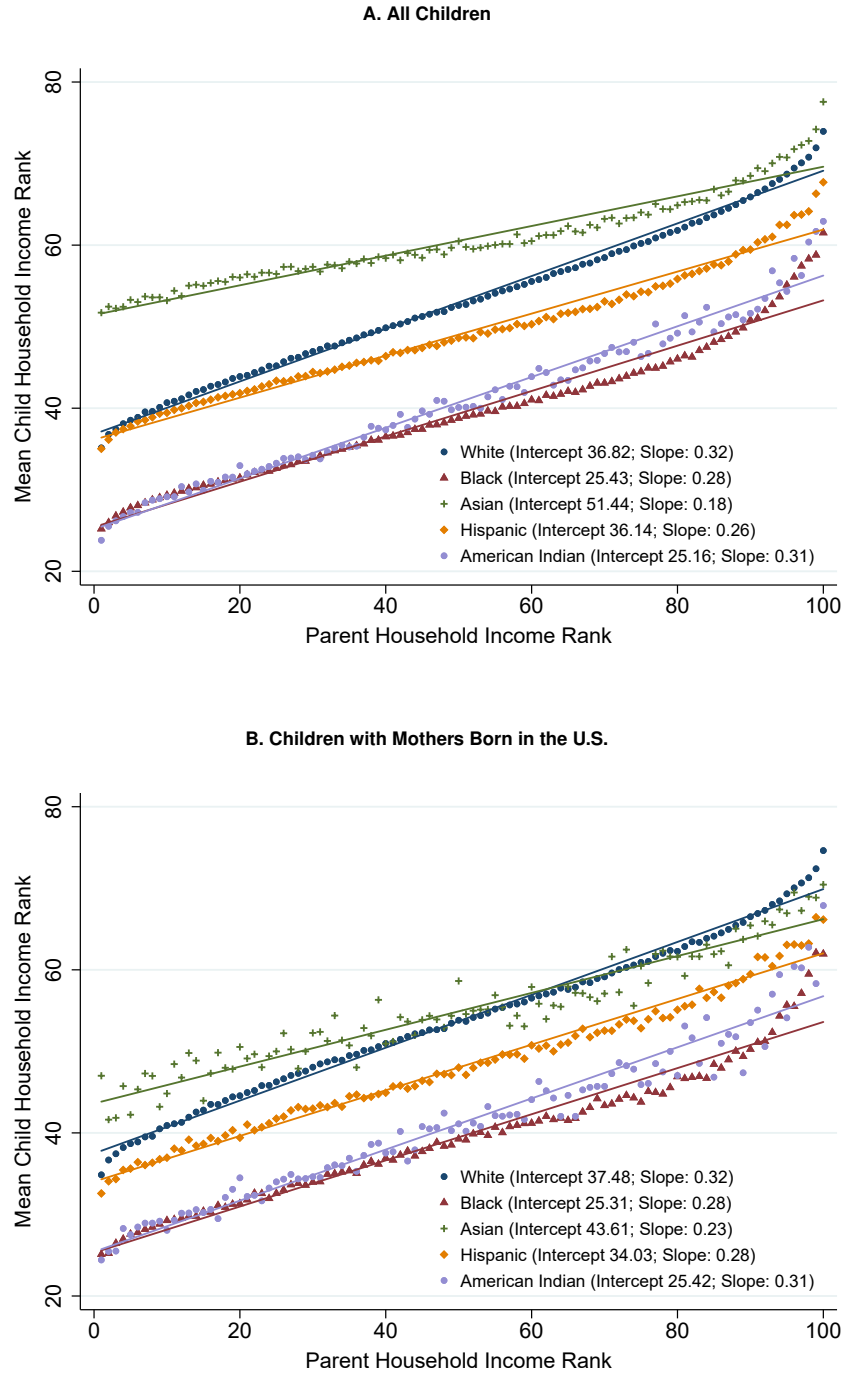
Notes: These figures show how rates of intergenerational mobility determine the evolution of racial disparities under the model in Section II. In Panel A, we assume that both black and white children have the same rates of relative and absolute intergenerational mobility. The solid line plots children's expected ranks conditional on their parents' ranks. We assume this line has a slope of 0.35, consistent with evidence from Chetty et al. (2014). Since mean ranks are 50 (by definition) for both parents and children, this line must pass through (50, 50). The steady-state mean income rank for both blacks and whites, depicted by the point where the solid line cross the dashed 45 degree line, is therefore 50. The figure illustrates convergence to this steady-state given mean ranks of 35 percentiles for black parents and 55 percentiles for white parents in the initial generation, depicted by the vertical lines. In this case, white children have a mean rank of 51.8 percentiles and black children have a mean rank of 44.8 percentiles in the next generation, depicted by the horizontal lines. The gap therefore falls from 20 percentiles to 7 percentiles in one generation. In Panel B, we assume that blacks and whites have the same rates of relative mobility ($\beta = 0.35$), but absolute mobility is 10 percentiles lower for blacks than whites ($\alpha_w - \alpha_b = 10$). Here, the steady-state for blacks is 42.3 percentiles, while the steady-state for whites is 57.7 percentiles; hence the intergenerational gap of $\Delta\alpha = 10$ leads to a steady-state racial disparity of 15.4 percentiles.

FIGURE II: Empirical Estimates of Intergenerational Mobility and Racial Disparities



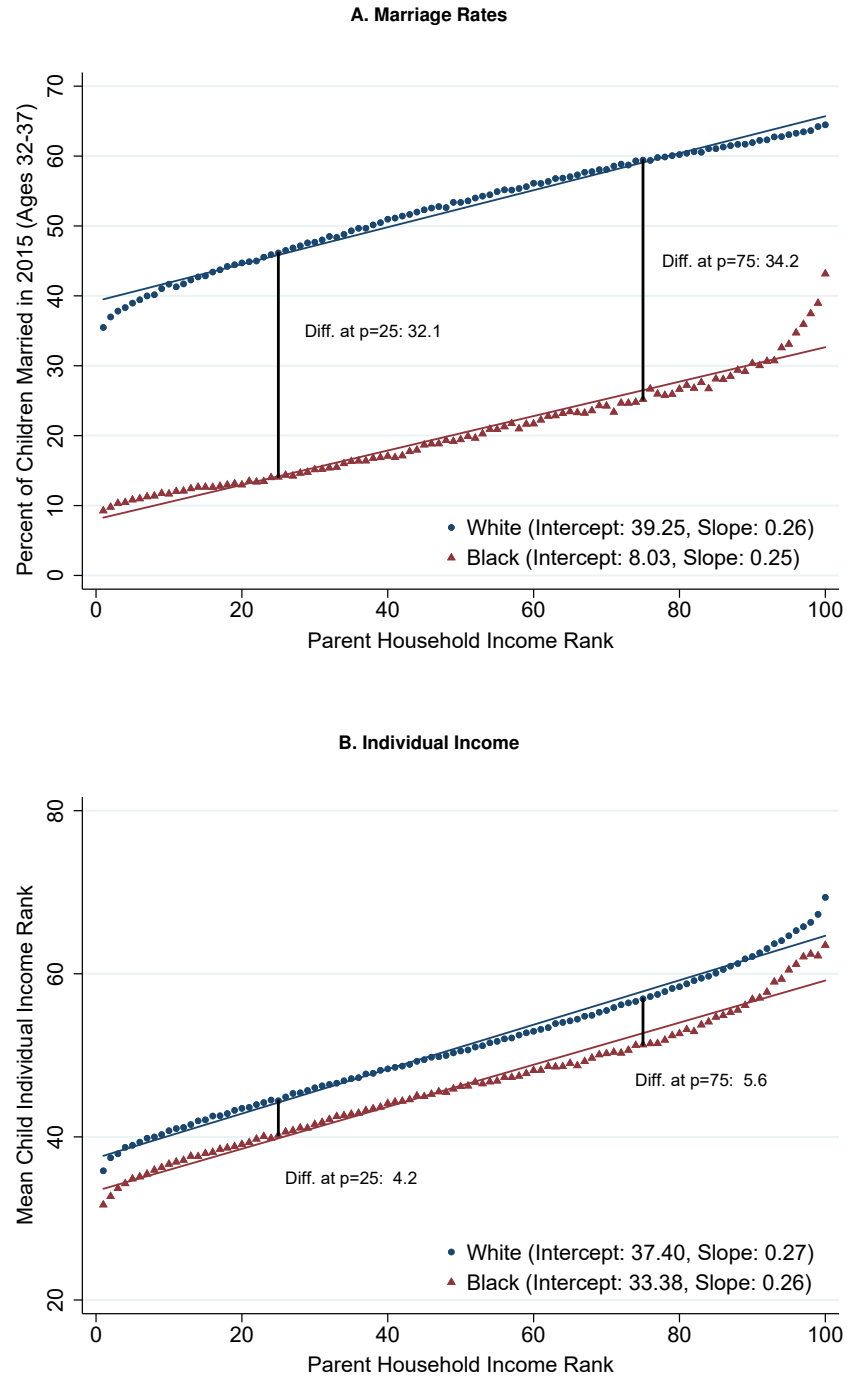
Notes: These figures show how empirical estimates of intergenerational mobility by race (Panel A) relate to the evolution of racial disparities (Panel B) using the model in Section II. These figures use the primary analysis sample (children in the 1978-83 birth cohorts). Child income is the mean of 2014-2015 household income (when the child is between 31-37 years old), while parent income is mean household income from 1994-1995 and 1998-2000. Children are assigned percentile ranks relative to all other children in their birth cohort, while parents are ranked relative to all parents with children in the same birth cohort. Panel A plots the mean household income rank of children by parent household income rank for black and white children. The best-fit lines are estimated using an OLS regression on the binned series; the slopes (β_r) and intercepts (α_r) from these regressions are reported for each race. We also report white-black differences in mean child individual income rank at the 25th, 75th, and 100th percentiles of the parent income distribution. Plugging the estimates of α_r and β_r into equation (3) from our model, the steady-state mean rank for blacks is $\frac{\alpha_b}{1-\beta_b} = 35.2$ percentiles, while the steady-state for whites is $\frac{\alpha_w}{1-\beta_w} = 54.4$ percentiles, resulting in a 19.2 percentile black-white gap in steady state. Panel B shows the empirically observed mean parent and child household ranks by race plotted against the predicted steady-state mean ranks for blacks, whites, and other racial groups. Estimates for Asians are based on the subsample of children whose mothers were born in the United States, as in Figure IIIb below. The circles show the unconditional mean income ranks for parents, while the diamonds show mean ranks for children in our analysis sample.

FIGURE III: Intergenerational Mobility by Race



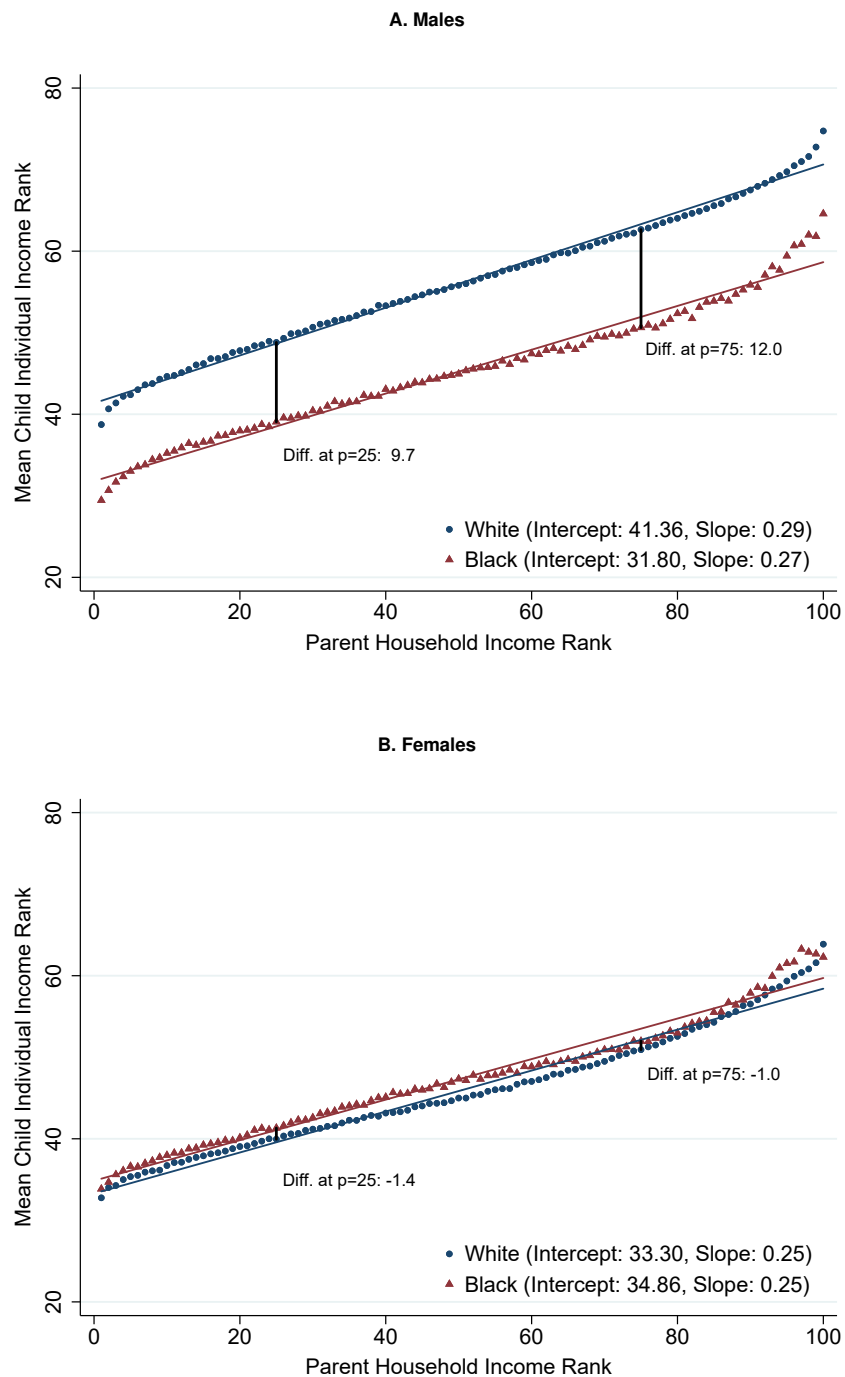
Notes: Panel A replicates Figure IIa, including series for Hispanics, Asians, and American Indians. Panel B replicates Panel A for children whose mothers were born in the U.S. Panel B is based on the subsample of children whose mothers appear in the 2000 Census long form or the 2005-2015 American Community Survey because information on parental birthplace is available only for those individuals. See notes to Figure II for further details.

FIGURE IV: Black-White Gaps in Marriage Rates and Individual Income



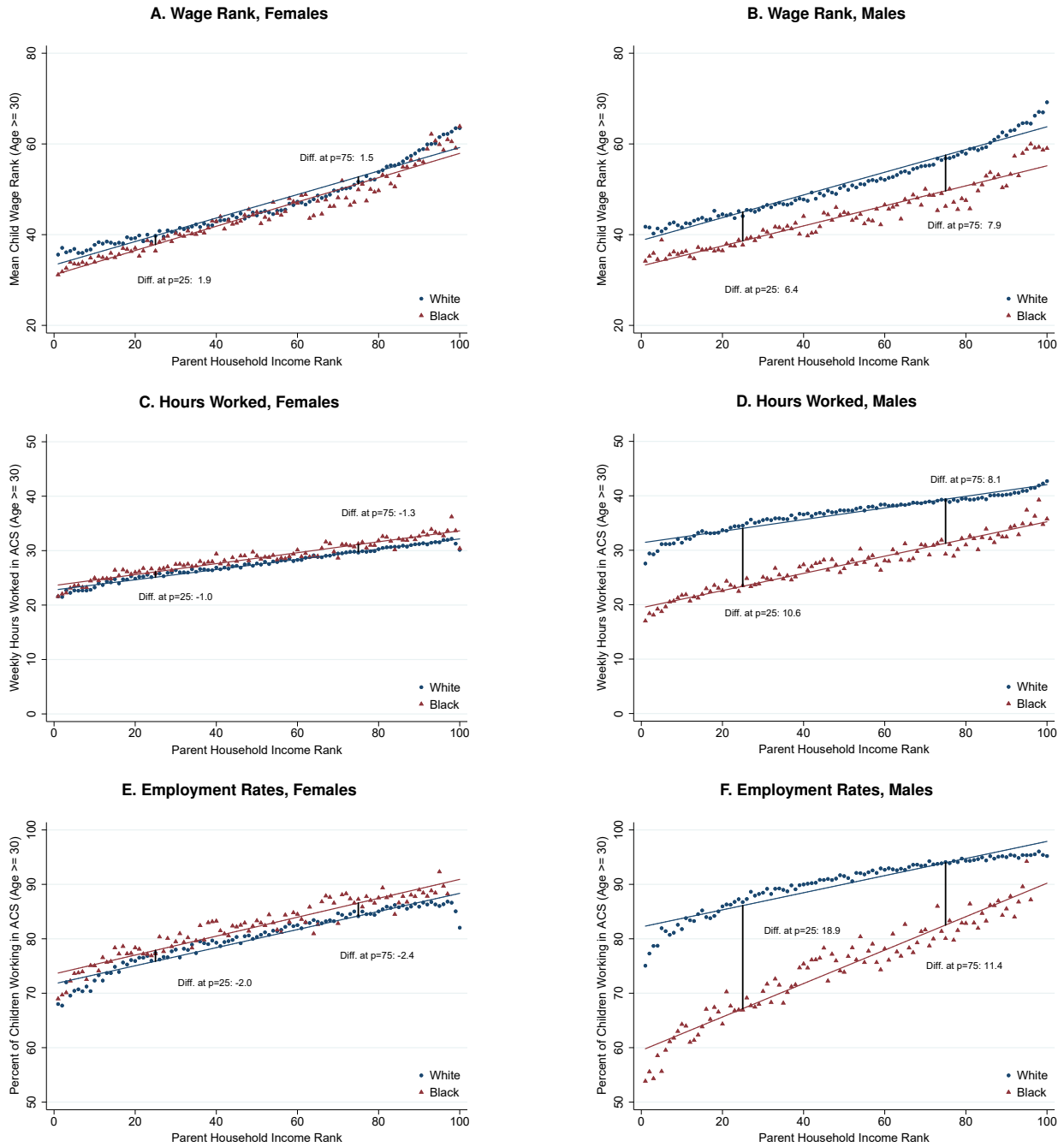
Notes: Panel A plots children's marriage rates by parent income percentile for black and white children. A child's marital status is defined based on the marital status used when filing his or her 2015 tax return. Children in our sample are between the ages of 32-37 at that point. Panel B plots the mean individual income rank of children vs. their parents' household income rank for black and white children. Individual income is defined as own W-2 wage earnings plus self-employment and other non-wage income, which is Adjusted Gross Income minus total wages reported on form 1040 divided by the number of tax filers (thereby splitting non-wage income equally for joint filers). We measure children's individual incomes as their mean annual incomes in 2014 and 2015. The intercepts, slopes, and best-fit lines are estimated using OLS regressions on the binned series. We also report the white-black differences in outcomes at the 25th and 75th parent income percentile. See notes to Figure II for further details on sample and variable definitions.

FIGURE V: Black-White Gaps in Individual Income, by Gender



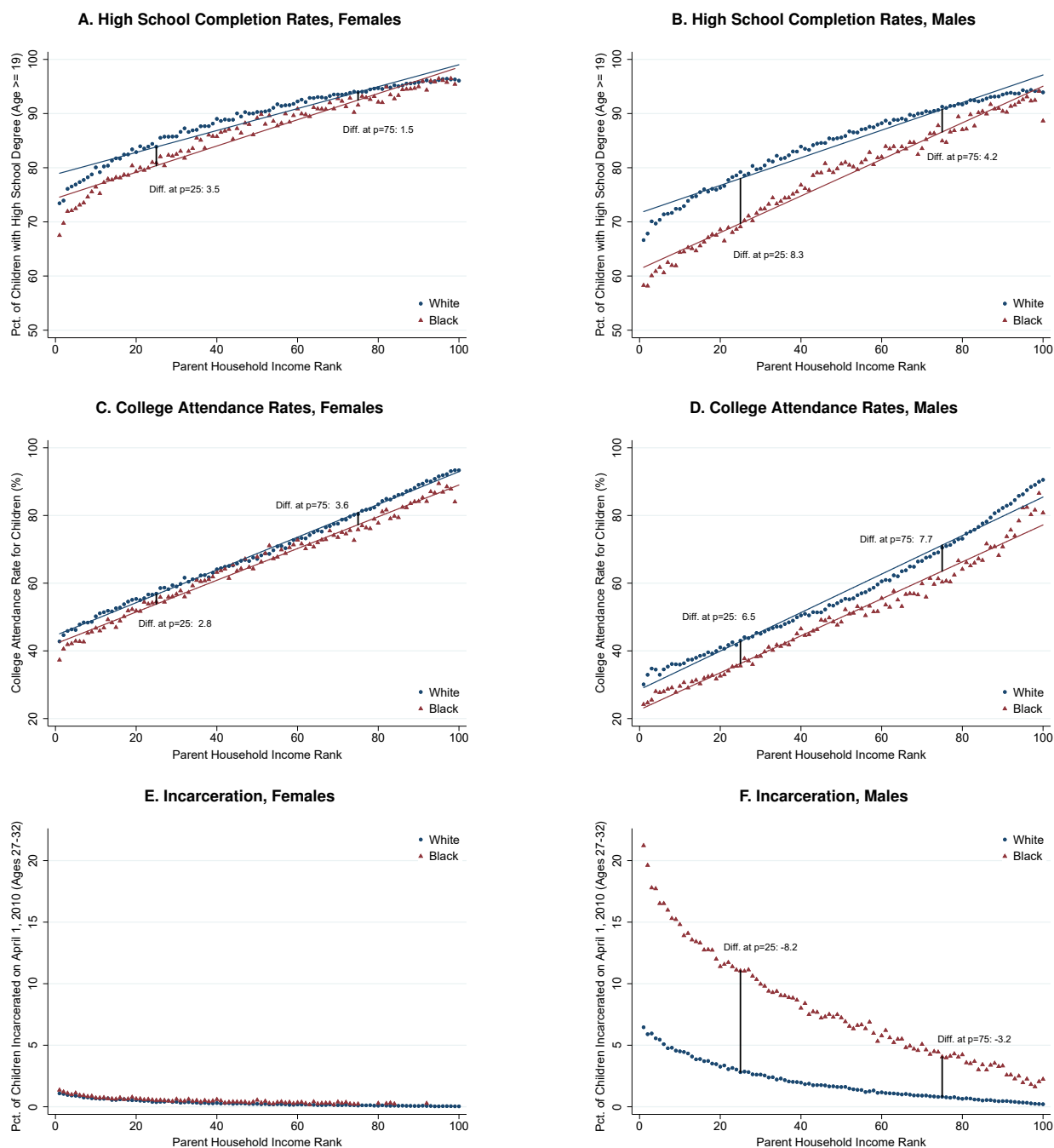
Notes: These figures replicate Figure IVb separately for male children (Panel A) and female children (Panel B). Individual income ranks are computed within a child's cohort pooling across race and gender. See notes to Figure IV for further details.

FIGURE VI: Black-White Gaps in Wage Rates, Hours, and Employment, by Gender



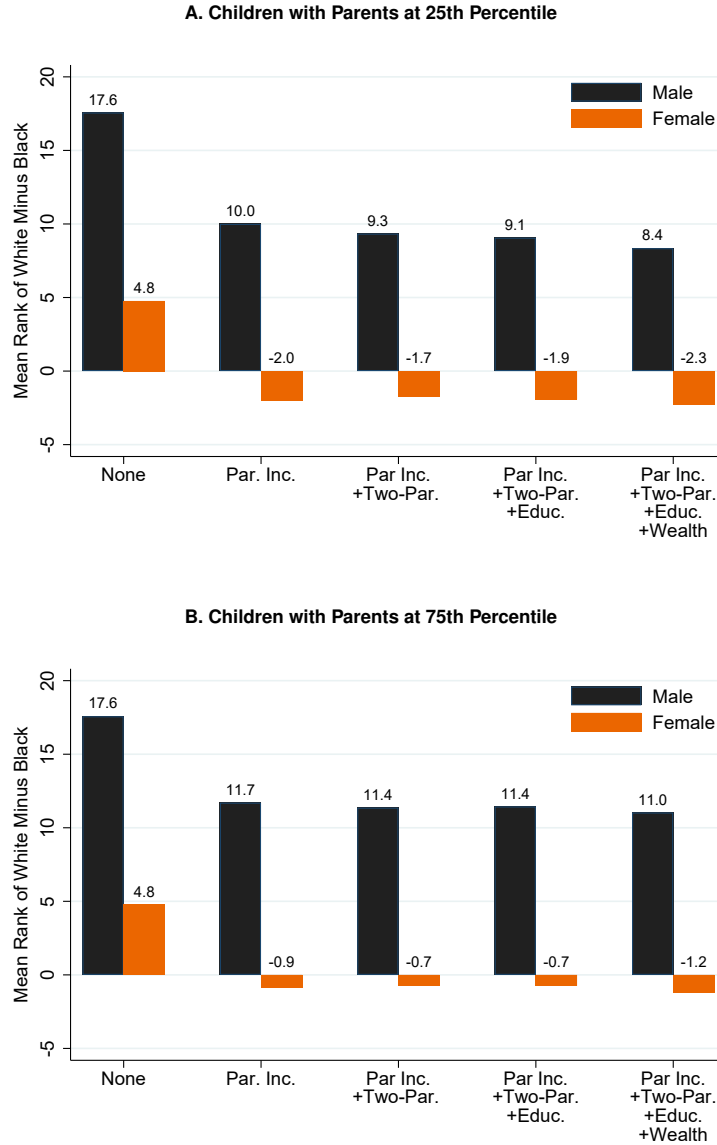
Notes: This figure shows the relationship between children's employment outcomes and their parents' household income, by race and gender. All children's outcomes in this figure are obtained from the American Community Survey and all panels include only children observed in the 2005-15 ACS at age 30 or older. Panels A and B plot mean wage ranks vs. parental household income percentile, by race and gender. Panels C and D replicate A and B using mean weekly hours of work as the outcome, while Panels E and F use annual employment rates as the outcome. Wages are computed as self-reported annual earnings divided by total hours of work; they are missing for those who do not work. We convert wages to percentile ranks by ranking individuals relative to others in the same birth cohort who received the ACS survey in the same year. Hours of work are defined as total annual hours of work divided by 51 and are coded as zero for those who do not work. Employment is defined as having positive hours of work in the past 12 months. To protect confidentiality, bins in which there are fewer than 10 children who are employed or not employed are suppressed in Panels E and F. In each figure, the best-fit lines are estimated using OLS regressions on the binned series. We report white-black differences based on the best-fit lines at the 25th and 75th parent income percentiles.

FIGURE VII: Black-White Gaps in Educational Attainment and Incarceration, by Gender



Notes: Panels A-D show the relationship between children's educational attainment and their parents' household income, by race and gender. Data on educational attainment is obtained from the American Community Survey. Panels A and B plot the fraction of children who complete high school by parental income percentile, by race and gender. Panels C and D replicate Panels A and B using college attendance as the outcome. Panels A-B include only children observed in the 2005-15 ACS at age 19 or older, while Panels C-D include those observed at age 20 or older. High school completion is defined as having a high school diploma or GED. College attendance is defined as having obtained "at least some college credit". Panels E and F plot incarceration rates vs. parent income percentile, by race and gender. Incarceration is defined as being incarcerated on April 1, 2010 using data from the 2010 Census short form. The children in our sample are between the ages of 27-32 at that point. The best-fit lines in Panels A-D are estimated using OLS regressions on the binned series. We report white-black differences based on the best-fit lines (in Panels A-D) and based directly on the non-parametric estimates (in Panel F) at the 25th and 75th parent income percentiles. To protect confidentiality, bins in which there are fewer than 10 children who exhibit the outcome or who do not exhibit the outcome are suppressed.

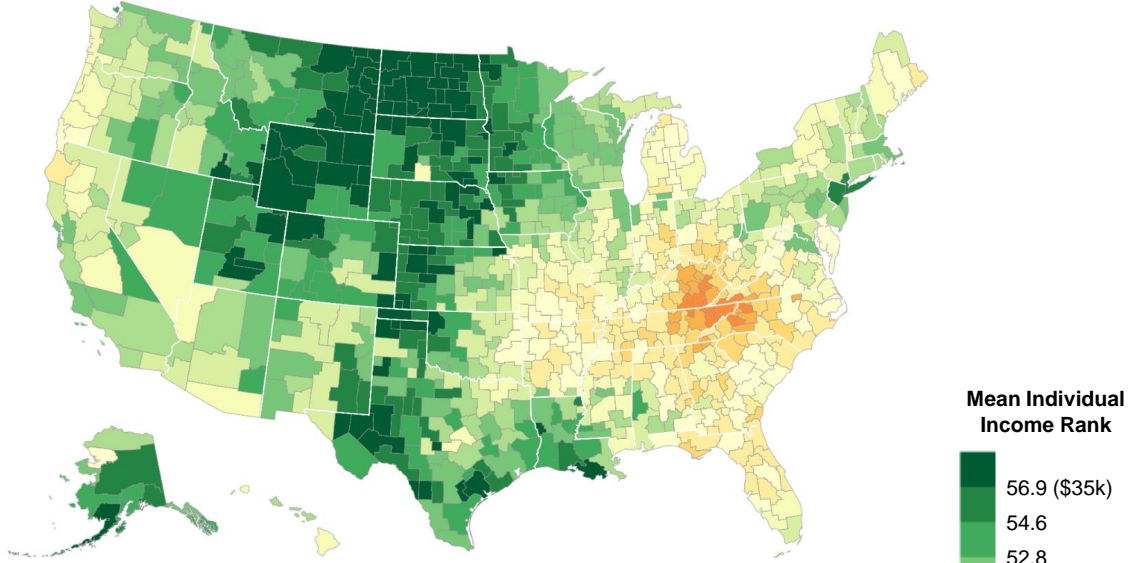
FIGURE VIII: Effects of Family-Level Factors on the Black-White Income Gap



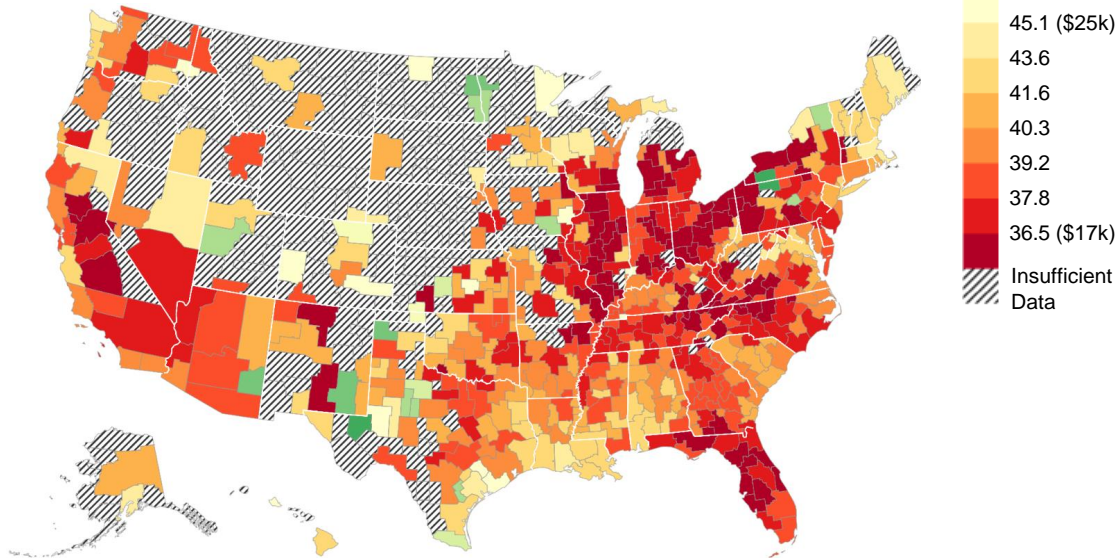
Notes: These figures show how the black-white gap in children's individual income ranks changes as we control for family-level factors. The bars on the left in each pair report the black-white gap in individual income ranks for boys, while the bars on the right report the same statistics for girls. The first set of bars show the unconditional black-white gap in mean individual income ranks. The second set of bars report $\Delta_{\bar{p}}$, the intergenerational gap in mean income ranks at percentile \bar{p} of the parental income distribution, estimated by regressing children's income ranks on their parents' ranks, an indicator for being white, and the interaction of these two variables. Panel A reports estimates for $\bar{p} = 25$, while Panel B reports estimates for $\bar{p} = 75$. The remaining bars report estimates of $\Delta_{\bar{p}}$ as we include additional controls in the regression: parental marital status, wealth, and education. Parental marital status is measured based on whether the primary tax filer who first claims the child as a dependent is married. We control for parental education using indicator variables for the highest level of education parents have completed using data from the ACS and the 2000 Census long form, prioritizing information from the ACS if both sources are available. We define seven categories of parental education: no school, less than high school, high school degree, college no degree, associate degree, bachelor degree and graduate degree. We use the mother's education if available; if not, we use the father's education. We control for parents' wealth using indicators for home ownership and the number of vehicles owned and linear controls for monthly mortgage payments and home value. These variables are also obtained from the 2000 Census long form and ACS, again prioritizing the mother's data. The estimates reported in the first three pairs of bars use the full analysis sample, while those in the fourth and fifth pairs of bars use the subsample for which the relevant controls are available from the 2000 Census and ACS.

FIGURE IX: The Geography of Upward Mobility in the United States, by Race

A. White Males with Parents at 25th Percentile

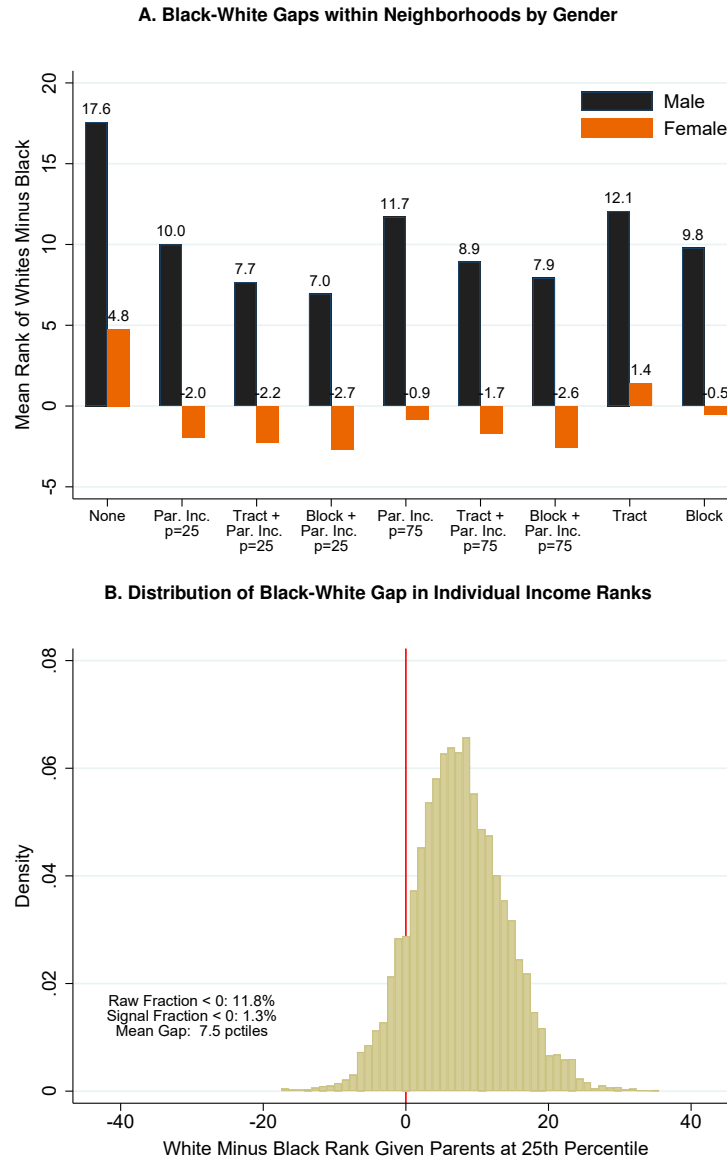


B. Black Males with Parents at 25th Percentile



Notes: These figures present maps of our baseline measure of intergenerational mobility by commuting zone (CZ). All figures are based on the same sample and income definitions as in Figure III. Children are assigned to commuting zones based on the first non-missing zip code of their parents (beginning when the child was claimed as a dependent), irrespective of where they live as adults. In each CZ, we regress children's individual income rank on a constant and parent income rank. Using the regression estimates, we define absolute upward mobility at the 25th percentile of the parent income distribution (r_{25}) as the intercept + $25 \times (\text{rank-rank slope})$. This corresponds to the predicted individual income rank for children with parents at the 25th percentile in a given CZ. The maps are constructed by grouping CZ-by-race observations into fifteen quantiles and shading the areas so that greener colors correspond to higher absolute mobility. Areas with fewer than 20 children in the core sample, for which we have inadequate data to estimate mobility, or fewer than 500 residents of the children's racial group in the 2000 Census are shaded with the cross-hatch pattern. The dollar amounts equivalent to the income ranks at the cutoffs are rounded to the nearest thousand (in 2015 dollars). Panel A shows the predicted individual income rank for white male children and Panel B for black male children.

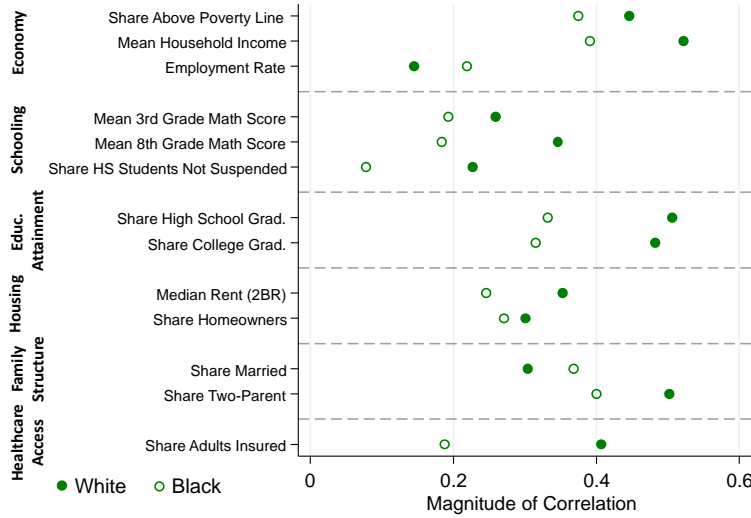
FIGURE X: Black-White Gaps within Neighborhoods



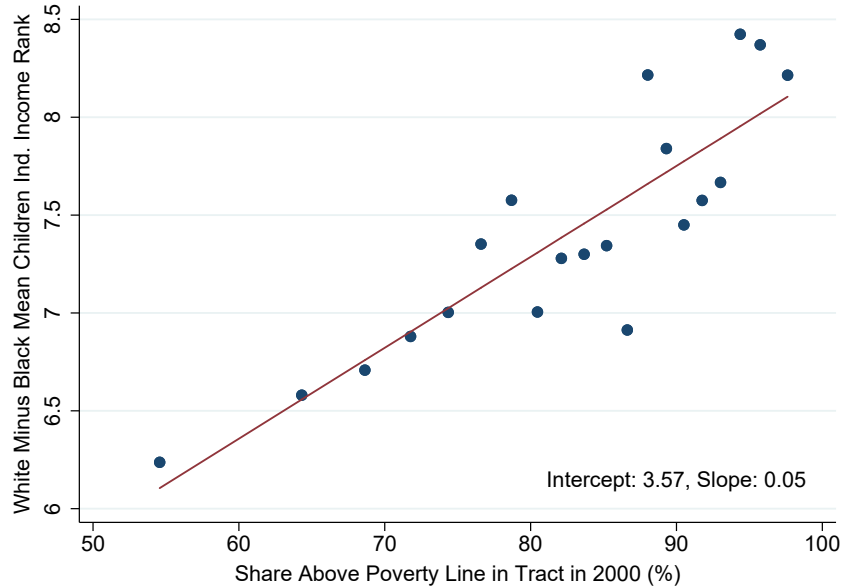
Notes: These figures show black-white gaps in individual income ranks controlling for parent income and childhood neighborhood, separately by child gender. The first set of bars in Panel A presents the raw, unconditional black-white gap. The second set of bars present the results from a regression in equation (5) in Section VI, plotting the coefficient of the indicator for the child race equal to white and its interaction with parent income, evaluated at $\bar{p} = 25$, $b_w + 0.25b_{wp}$, separately for males and females. The third set of bars again plot $b_w + 0.25b_{wp}$ from equation (5) but also includes Census tract fixed effects. The fourth set of bars are analogous to the third set of bars, replacing the Census tract fixed effects with Census block fixed effects. The fifth, sixth and seventh sets of bars replicate the second, third and fourth sets of bars, but for $\bar{p} = 75$ instead of $\bar{p} = 25$. The eighth and ninth sets of bars plot the coefficient of an indicator for white children of a regression of child income rank on an indicator for white children and Census tract or Census block fixed effects. Panel B plots the distribution of the difference in the tract-level estimates of predicted individual income ranks for white vs. black male children with parents at the 25th percentile of the parental income distribution. Each observation is weighted by the number of black male children in the sample underlying the predicted rank estimates. We exclude Census tracts for which child income ranks were constructed with fewer than 50 black or white male children. We report the mean gap in predicted income ranks between white and black male children, and the raw and noise-corrected estimate of the fraction of black males growing up in Census tracts where the predicted income rank for black males is higher than for white males.

FIGURE XI: Outcomes for White vs. Black Males with Parents at 25th Percentile, by Tract

A. Correlations between Tract-Level Covariates and Individual Income Rank for Black Males vs. White Males

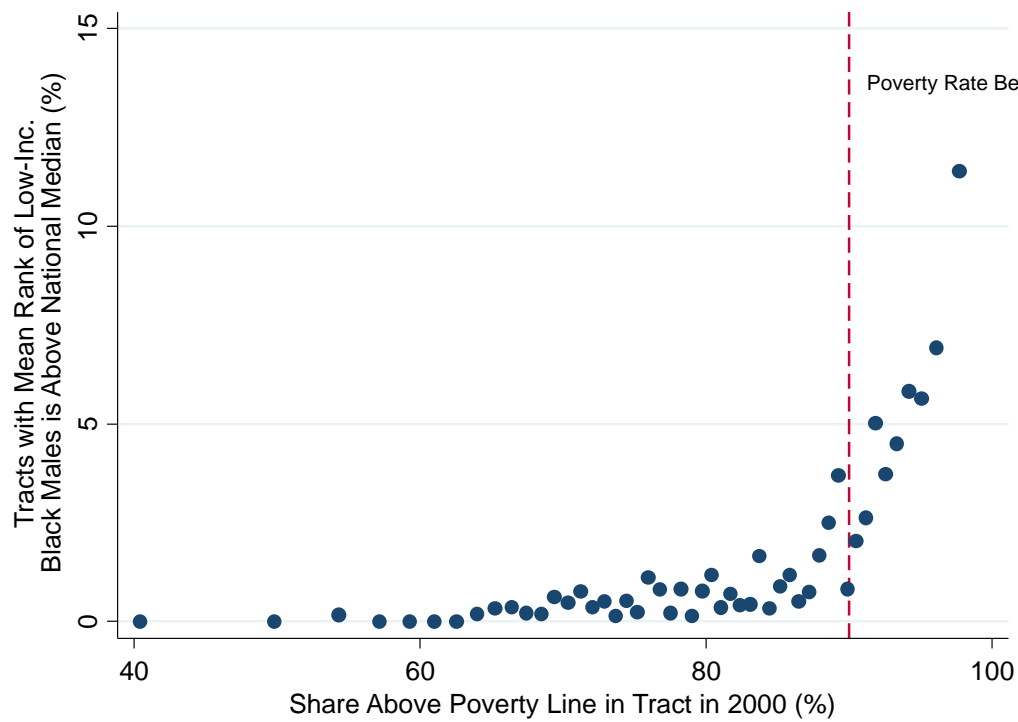


B. Black-White Gap in Mean Individual Income Rank vs. Share Above Poverty Line



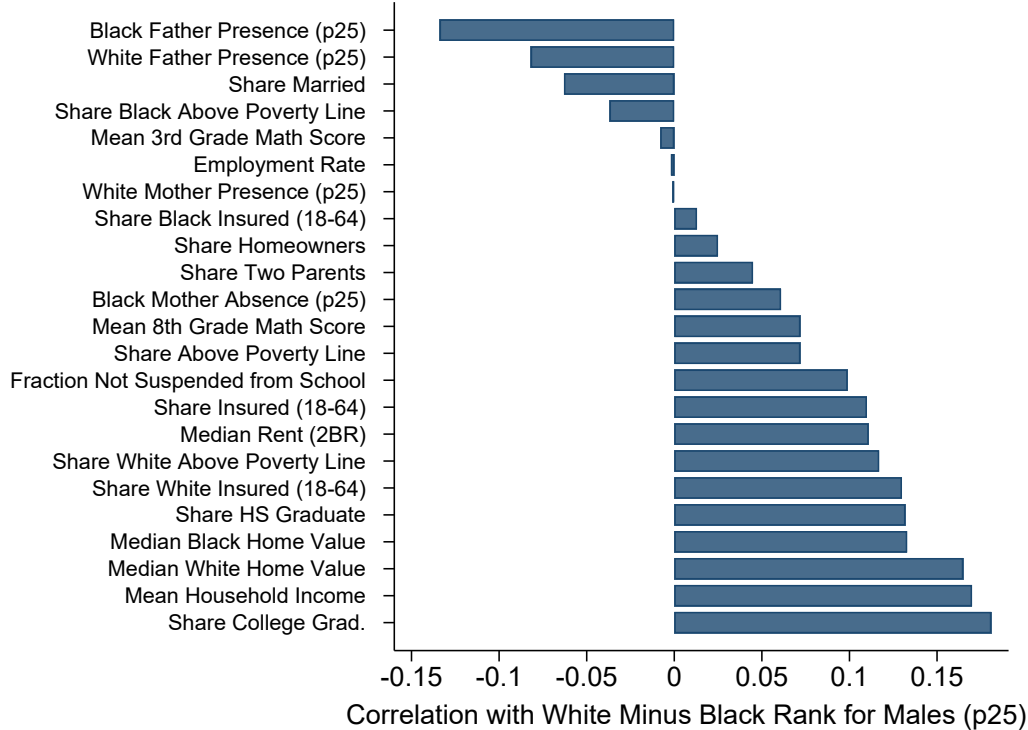
Notes: Panel A presents correlations of $\alpha_r^c + 0.25\beta_r^c$ for individual incomes of black and white males across tracts with selected covariates. See Appendix C for variable sources and definitions. Hollow circles present the coefficients for black males and filled circles present correlations for white males. The coefficients are signal correlations adjusting for sampling error, and use precision weights. To calculate the signal correlations, the raw correlations are rescaled by the reliability ratio, the ratio of signal variance to total variance of the $(\alpha_r^c + 0.25\beta_r^c)$ estimates. The correlations for black males are done on the set of tracts for which more than 20 black men are used to calculate $(\alpha_r^c + 0.25\beta_r^c)$, whereas the white male correlations are done on the set of tracts with at least 20 white males. Panel B presents a binned scatter of the mean black-white intergenerational gap at $\bar{p} = 25$, $\alpha_w^c + 0.25\beta_w^c - \alpha_b^c + 0.25\beta_b^c$, in each tract as a function of the share above the poverty line. The sample contains all tracts with at least 20 white males and 20 black males in our sample, along with a non-missing share above the poverty line taken from the 2000 Census. Tracts are binned into ventiles, weighting each tract by the number of black men used in the calculation of the black-white intergenerational gap. The best fit line is calculated using an OLS regression on the binned tract values.

FIGURE XII: Fraction of Tracts in which Predicted Rank of Black Males is above National Median vs. Share above Poverty Line



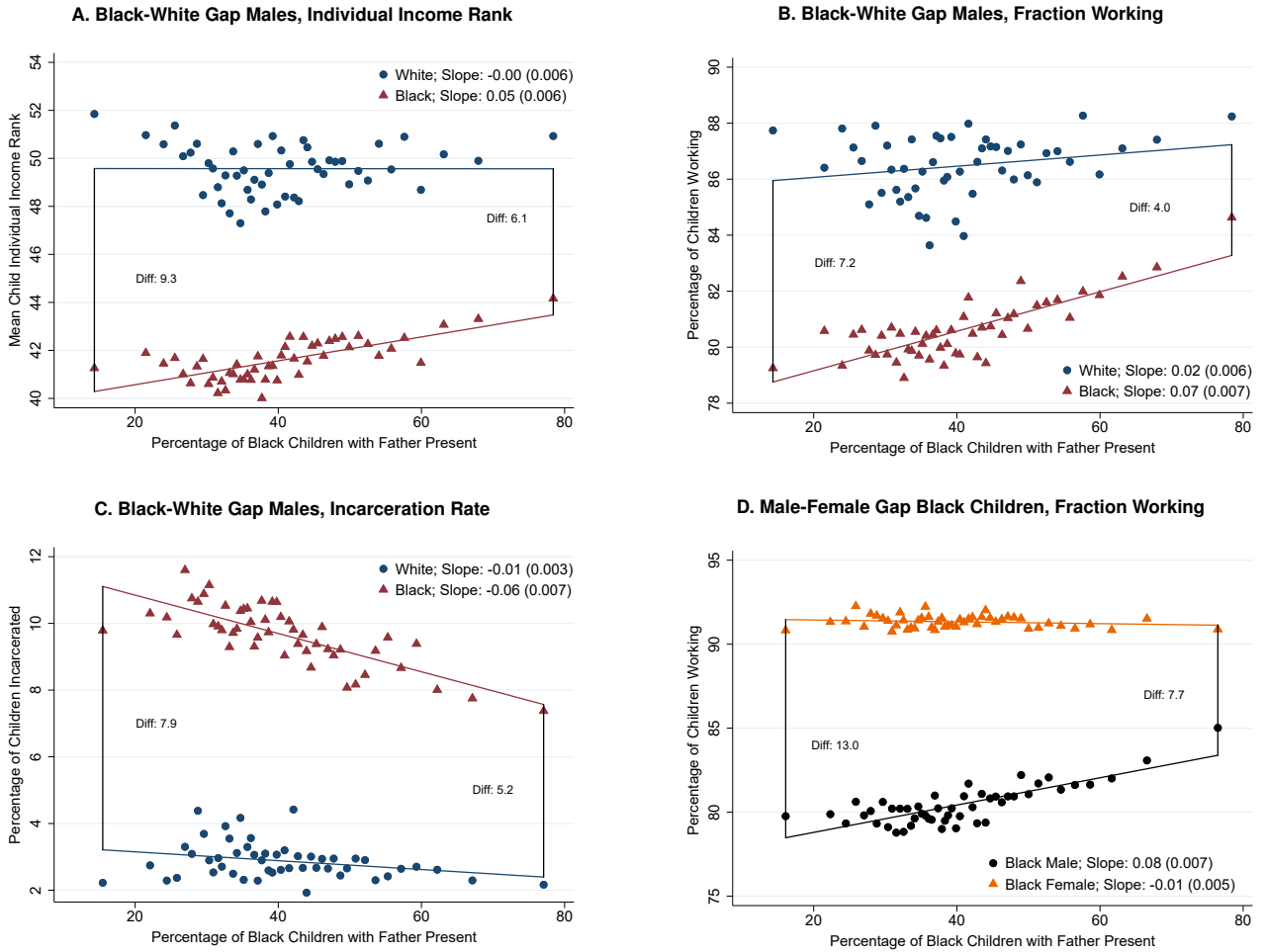
Notes: This figure presents a non-parametric binned scatter plot of the relationship between the fraction of Census tracts in which the predicted rank of black males is above the national median, $1\{\alpha_b^c + 0.25\beta_b^c > 0.5\}$, and the share of people above the poverty line in a given Census tract. The sample contains tracts with at least 50 black males and a non missing share above the poverty line. Tracts are grouped into 50 bins, weighting by the number of black males in the tract.

FIGURE XIII: Covariates Correlated with Black Male Income and Black-White Gap



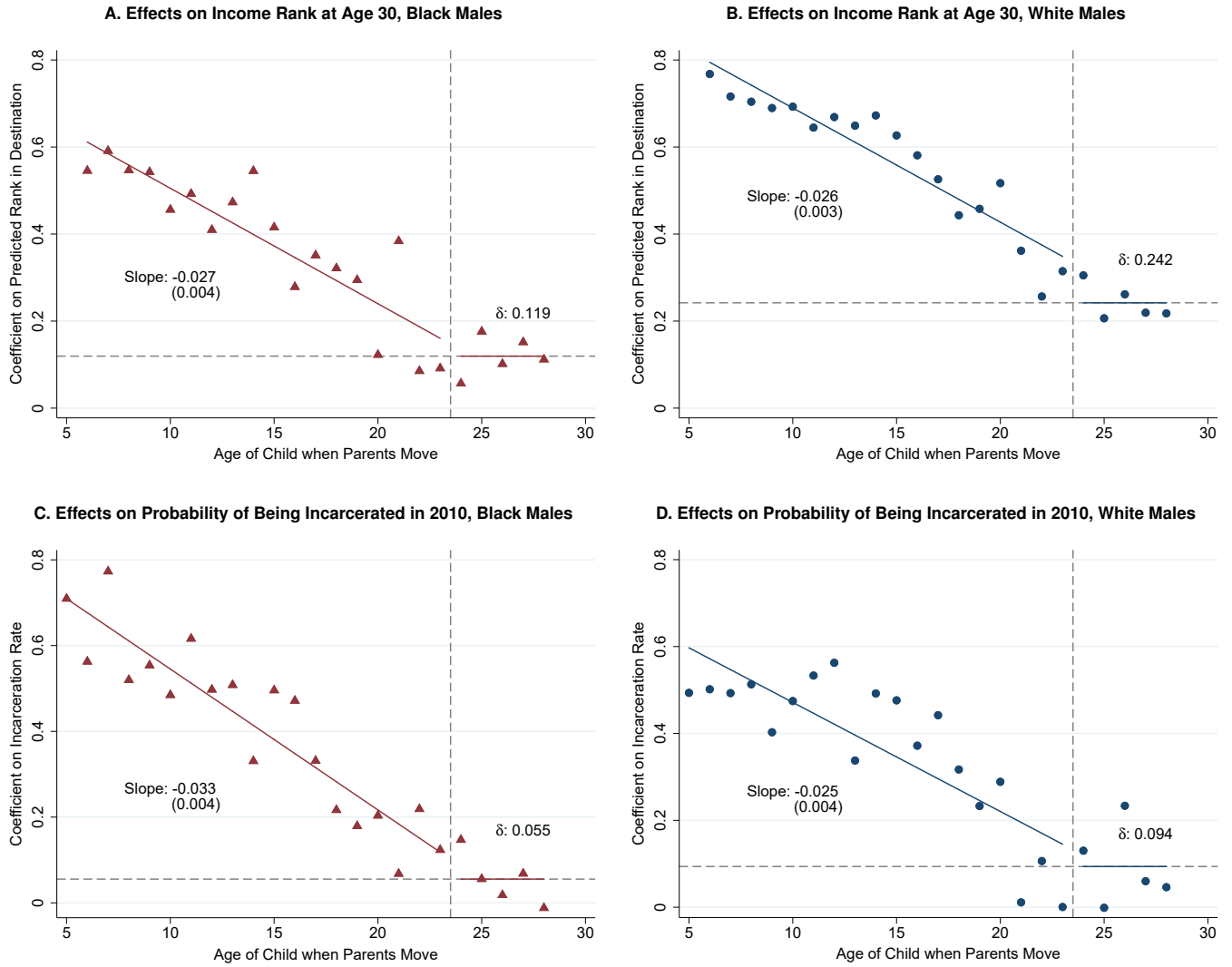
Notes: This figure presents the relationship between a set of covariates and the black-white intergenerational gap for males with parents at $\bar{p} = 25$, as measured by $\alpha_w^c + 0.25\beta_w^c - \alpha_b^c + 0.25\beta_b^c$. We restrict to covariates with correlations of the same sign at both $\bar{p} = 25$ and $\bar{p} = 75$. All variables are defined such that their correlation with the level of outcomes for black males is positive. We restrict to Census tracts with poverty rates below 10% from the 2000 Census publicly available tract level data. All correlations are at the tract-level and are weighted by the precision of the estimated intergenerational gaps. The coefficients are signal correlations adjusting for sampling error. Negative correlations correspond to smaller magnitudes of intergenerational gaps.

FIGURE XIV: Racial Disparities and Father Presence in Low Poverty Tracts, Children with Parents at 25th Percentile



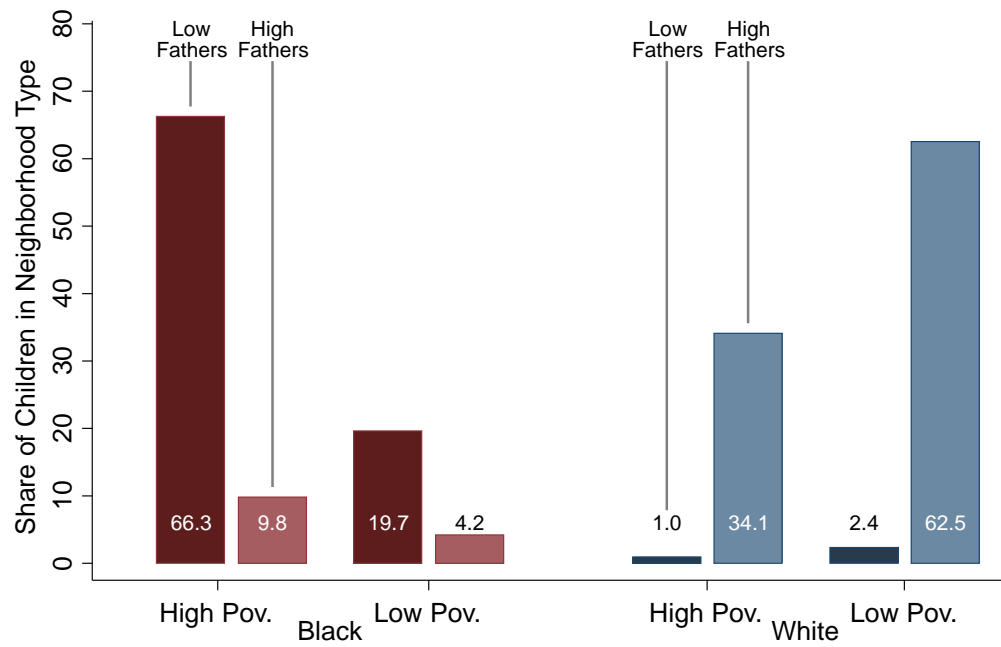
Notes: These figures present binned scatter plots of the relationship between various child outcomes and the percentage of black children growing up in the presence of a father in low poverty Census tracts. We define low poverty tracts as those with a poverty rate of less than 10% from the 2000 Census publicly available tract level data. In each panel, the share of black males with parents at the 25th percentile of the national income distribution who have their father present in childhood is binned into 50 quantiles and plotted on the x-axis. Panel A plots the mean child individual income rank on the y-axis, Panels B and D plots the percentage of children working (panel not working is defined as having zero individual income in 2014 and 2015), and Panel C shows the percentage of children incarcerated on April 1, 2010. We restrict to tracts with at least 20 observations for both white and black males in Panels A, B, and C, and 20 observations for both black males and females in Panel D. We estimate best fit lines on the binned points using OLS and report gaps on the predicted values at the 1st and 50th quantile. We also report the slope coefficients and standard errors (in parentheses).

FIGURE XV: Effect of Childhood Exposure on Income and Incarceration in Adulthood



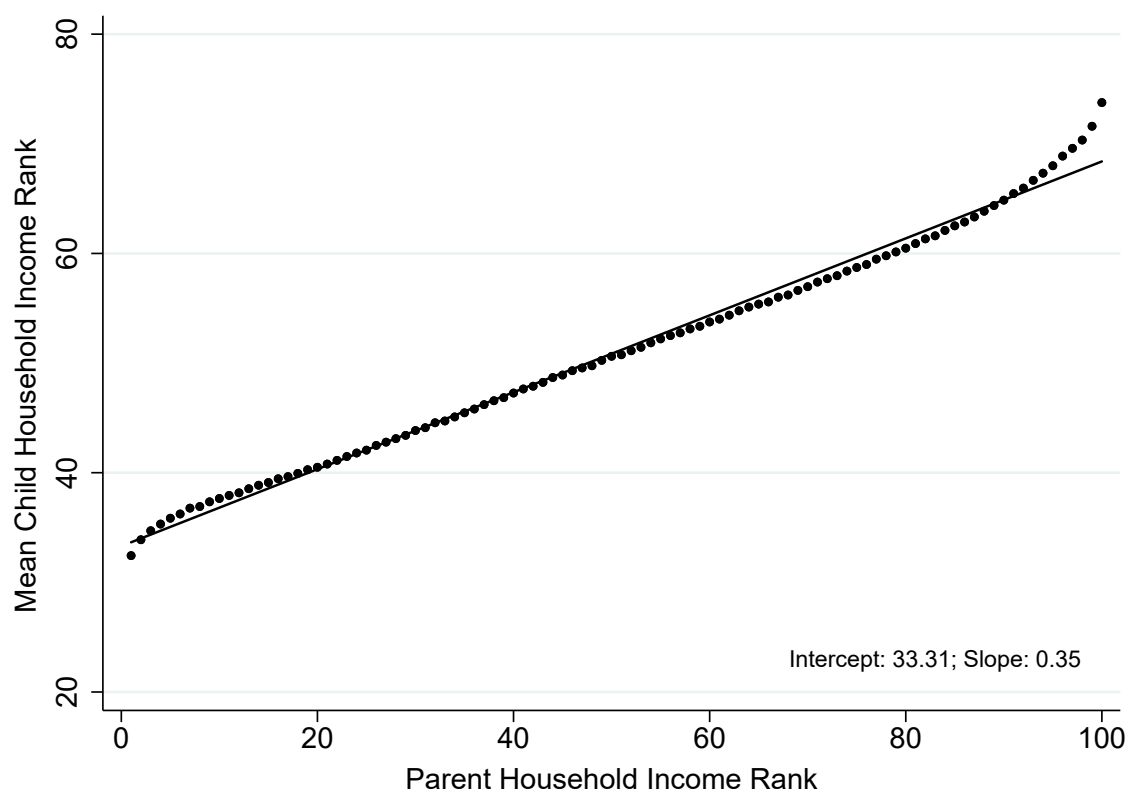
Notes: These figures show the effect of childhood exposure to different CZs on income and incarceration in adulthood. See Section VIIC for the exact regression specification. Each figure plots the coefficients, b_m , from equation (7) for each age of the child, m , at the time of the move. The sample consists of male children born between 1978-1986 who are identified as having moved once across CZs from their parents' tax records. Panel A presents the results for individual income at age 30 for black males, Panel B analogously for white males. For those two panels, the sample is restricted to birth cohorts 1978-1985 for whom income at age 30 is observed. Panel C and D plot the coefficients for incarceration in 2010. We restrict this sample to those for whom we are able to observe incarceration in 2010 prior to age 23. Best fit lines are presented using regressions on the coefficients, b_m , separately for $m \leq 23$ and $m > 23$. In some cases, the slopes reported differ from Table 4 slightly because they are estimated from a regression on the coefficients, b_m , as opposed to a linear parametrization on the individual level data.

FIGURE XVI: Father Presence and Poverty Rates by Tract



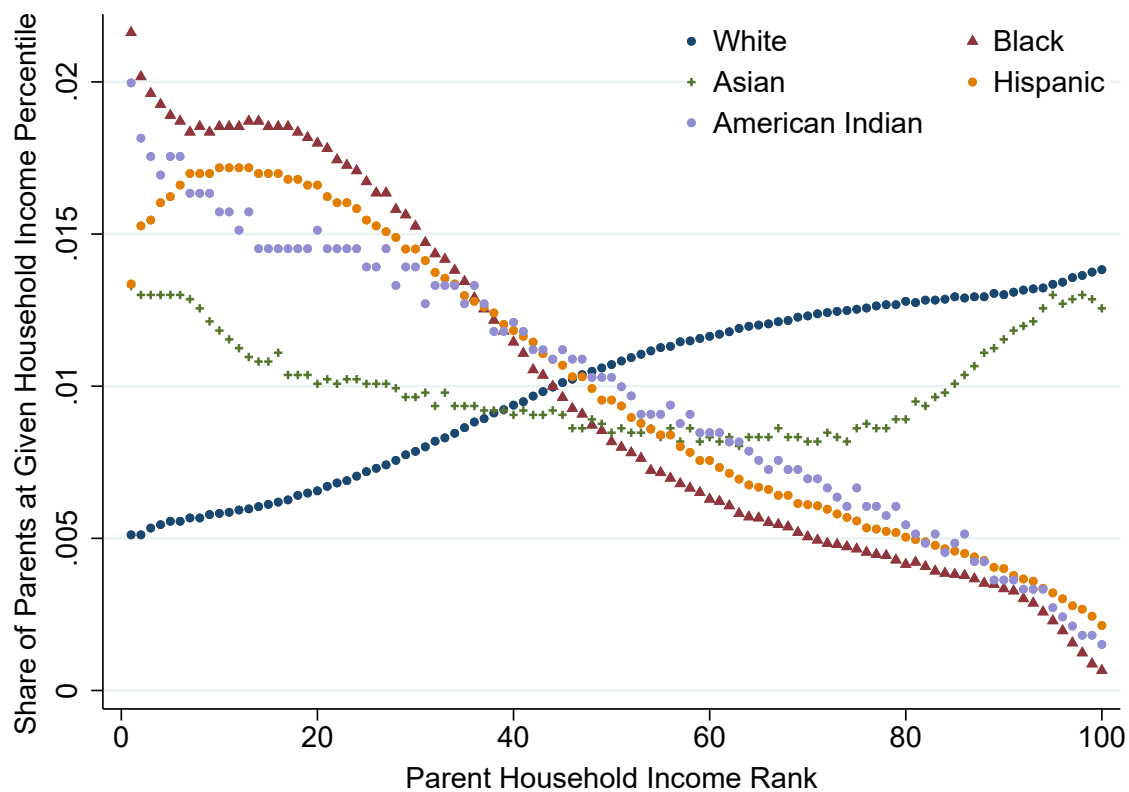
Notes: This figure presents the share of Census tracts by poverty share and father presence by race. We define Census tracts with “high father presence” as those with more than 50% of fathers present in families among children of the same race. Low-poverty tracts are those with a poverty rate of less than 10% from the 2000 decennial Census.

ONLINE APPENDIX FIGURE I: Intergenerational Mobility in the Full Population



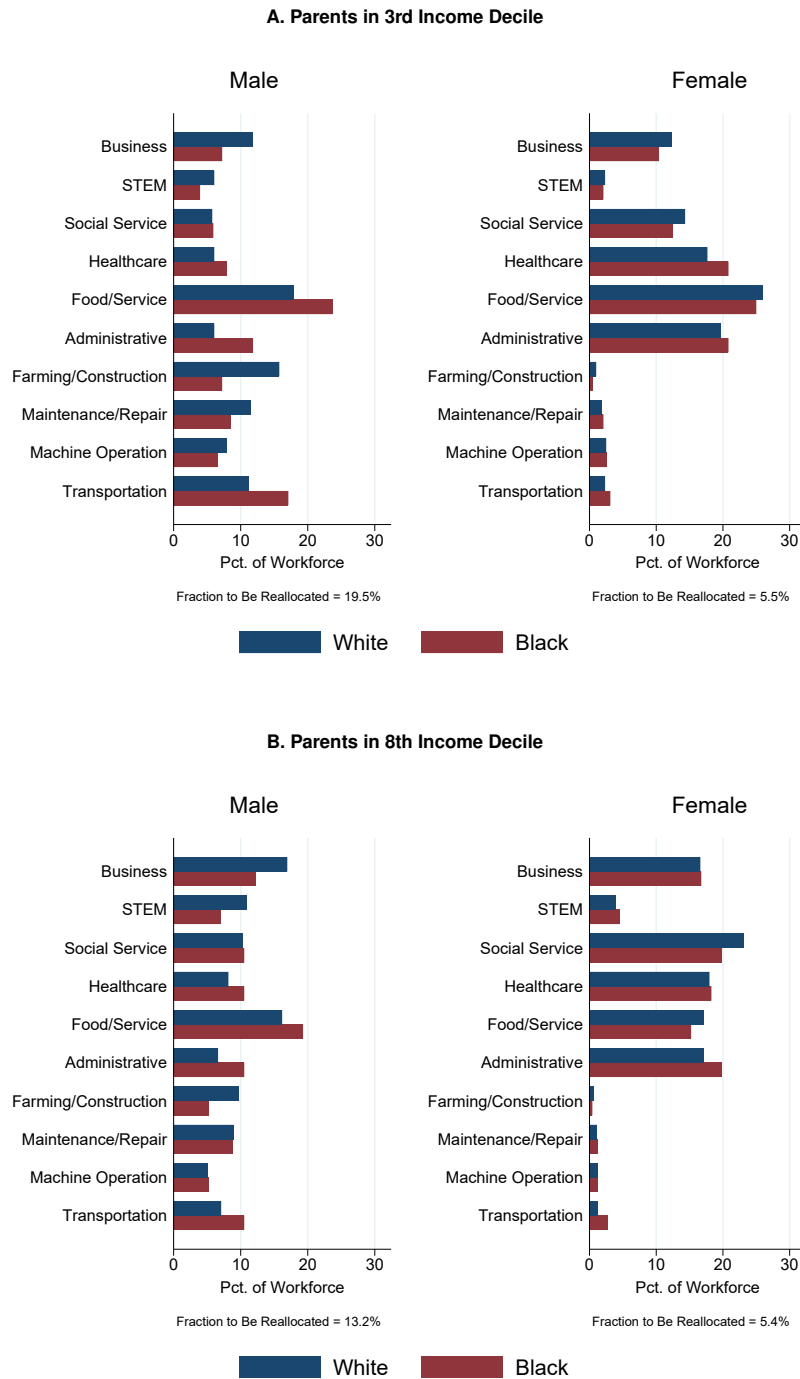
Notes: This figure plots the mean household income rank of children vs. parent household income rank in the full population, pooling all races and genders. The best-fit lines are estimated using an OLS regression on the binned series. See notes to Figure II for details on variable and sample definitions.

ONLINE APPENDIX FIGURE II: Density of Parent Household Income Ranks by Race



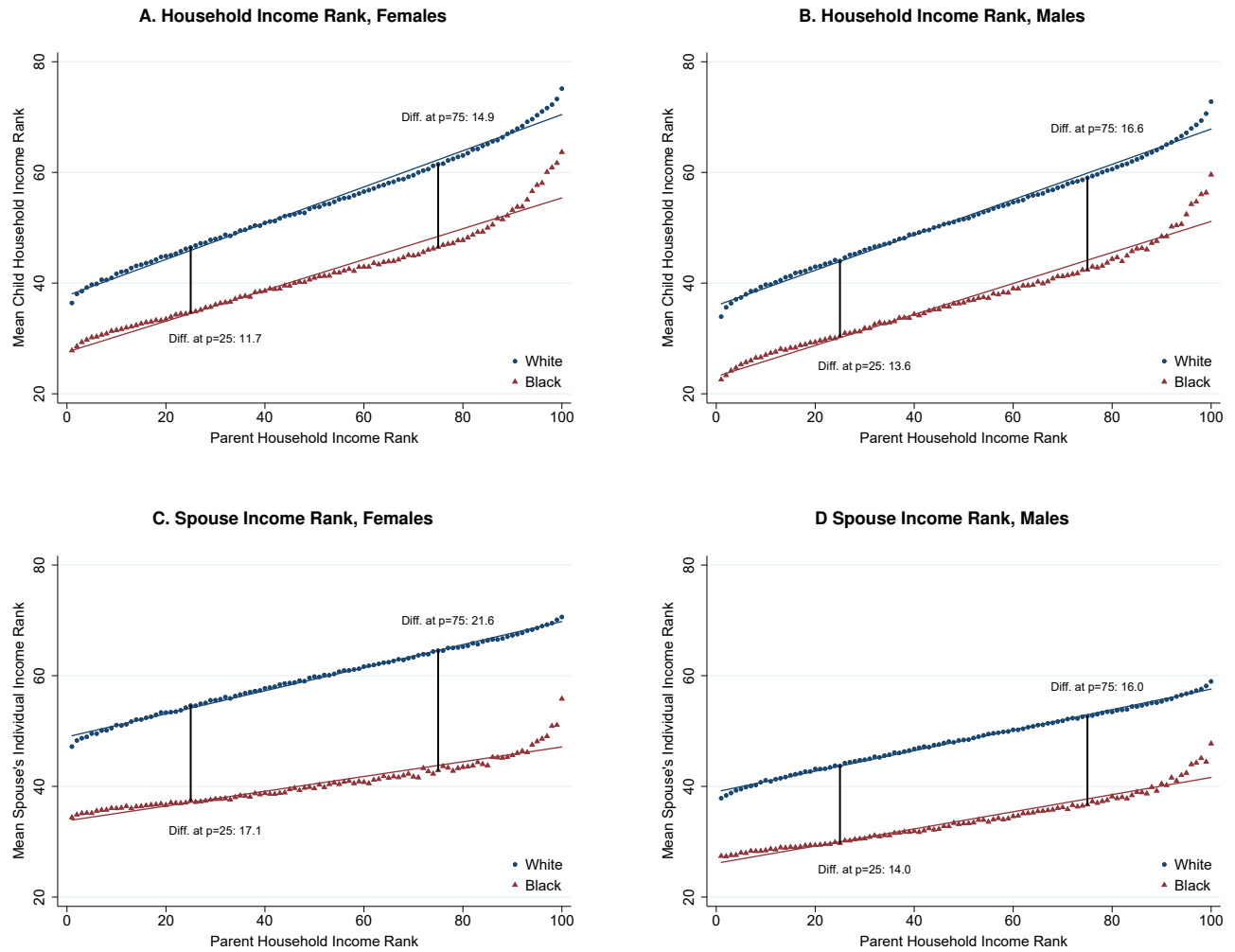
Notes: This figures plots the fraction of kids, by race, within each parent income rank using our baseline definition of parental household income.

ONLINE APPENDIX FIGURE III: Occupational Distributions Conditional on Parent Income, by Race and Gender



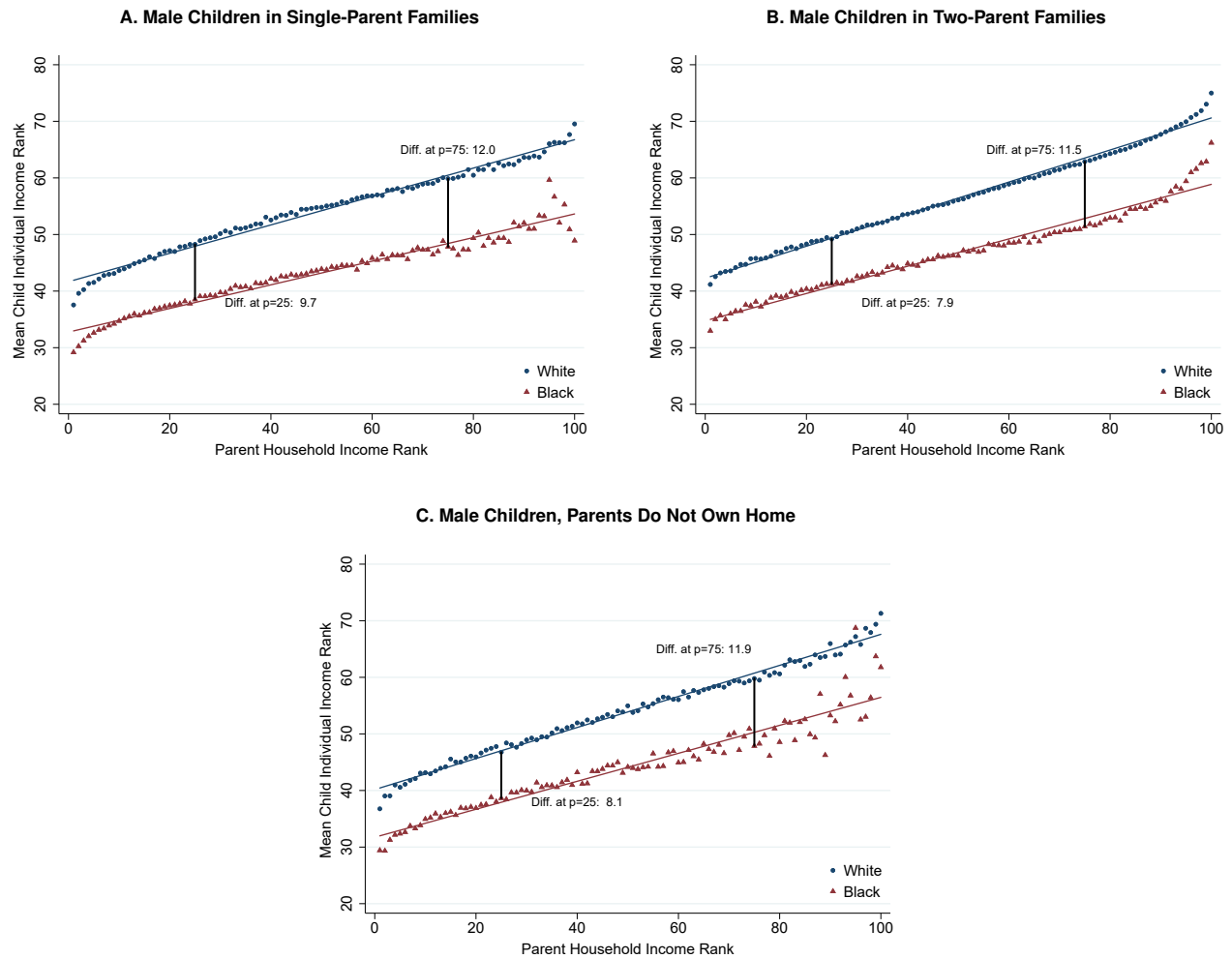
Notes: This figure plots the distribution of occupations by race and gender for black and white children. The sample consists of children whom we observe in the ACS at age 30 or older and who report working in the previous year in the ACS. Occupations are coded using the one-digit ACS occupation codes. In Panel A, we focus on children with parents in the third decile of the household income distribution; in Panel B, we focus on children with parents in the 8th decile. We use our baseline definition of parent household income ranks in this analysis. For each parent income decile and race, we also report the minimum fraction of people of black workers that would have to be reallocated in order to match the occupational distribution of white workers.

ONLINE APPENDIX FIGURE IV: Intergenerational Gaps in Household and Spousal Income, by Gender



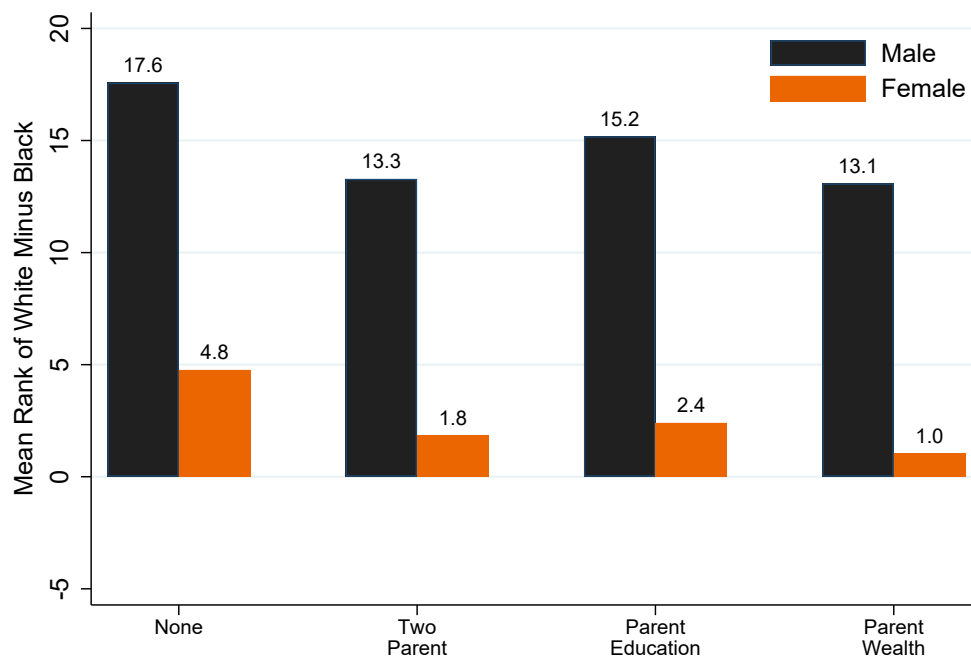
Notes: This figure replicates Figure V using children household income ranks (Panels A and B) and spousal income ranks (Panels C and D) instead of individual income ranks. Spousal income is defined as child household income minus child individual income; children who are not married are assigned spousal income of 0 and are included in the figures. See notes to Figure V for further details.

ONLINE APPENDIX FIGURE V: Black-White Intergenerational Gaps, Controlling for Parental Marital Status and Wealth



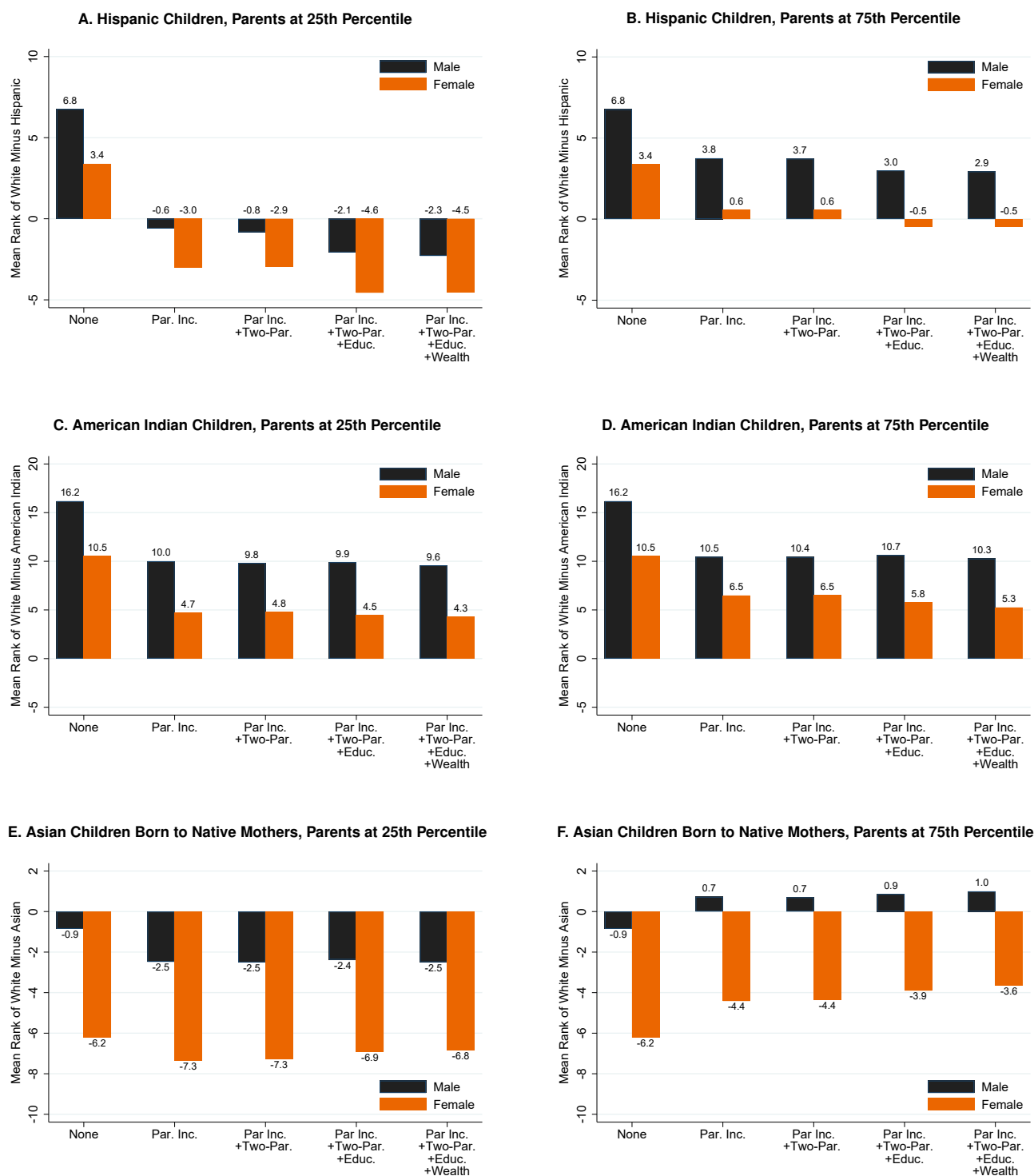
Notes: These figures replicate Figure Va for male children in single-parent families (Panel A), two-parent families (Panel B), and among parents who do not own a home (Panel C). See notes to Figure Va for further details and Section III for definitions of parental marital status and home ownership. The best-fit lines are estimated using an OLS regression on the binned series.

ONLINE APPENDIX FIGURE VI: Effects of Family-Level Factors on the Unconditional Black-White Gap



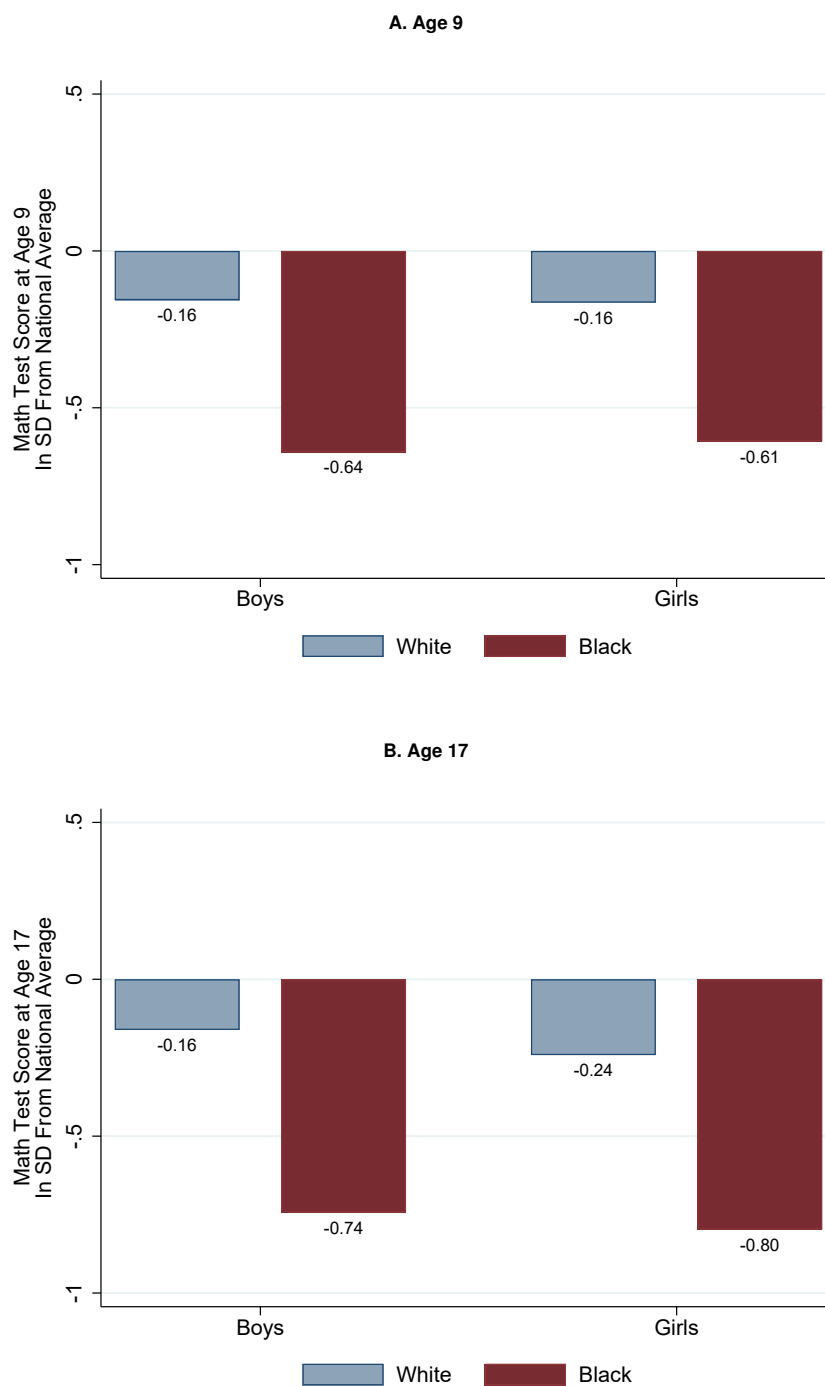
Notes: This figure shows how the black-white gap in children's individual income ranks changes as we control for family-level factors, without conditioning on parental income. Each bar plots an estimate from an OLS regression of children's individual income ranks on an indicator for being white and a single set of additional control variables. The first pair of bars show the unconditional black-white gap in mean individual income ranks for male and female children, respectively. The subsequent bars show how the coefficients on the white child indicator changes as additional controls are added. We use the same three groups of controls as in Figure VIII, but include only one group of controls in each regression (without controlling for parental income). See notes to Figure VIII for definitions of the control variables.

ONLINE APPENDIX FIGURE VII: Effects of Family-Level Factors on Intergenerational Gaps



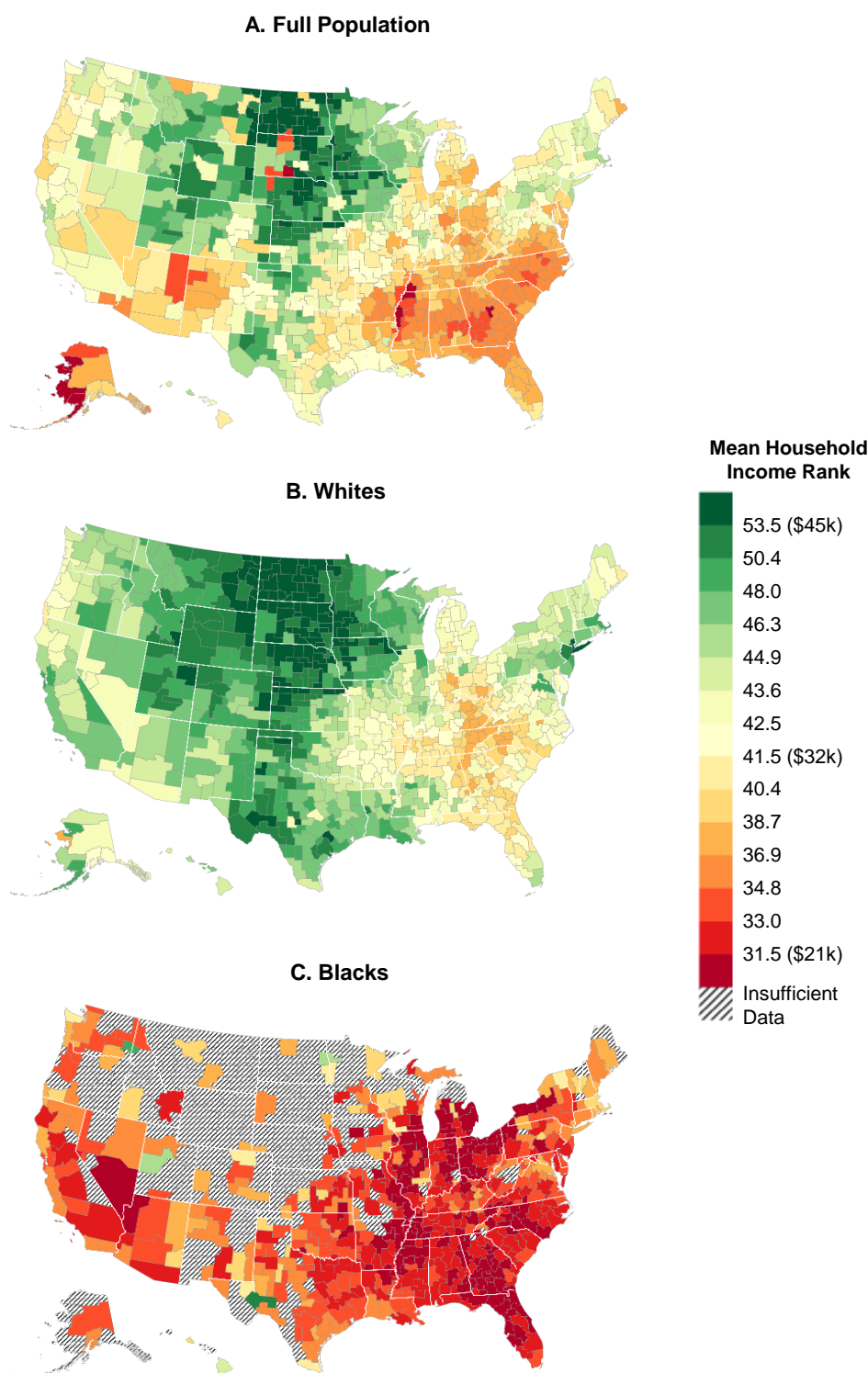
Notes: These figures replicate Figure VIII for Hispanic children (Panels A-B), American Indian children (Panels C-D), and Asian children whose mothers were born in the U.S. (Panels E-F). All panels show gaps for the relevant group relative to whites. See notes to Figure VIII for further details.

ONLINE APPENDIX FIGURE VIII: Black-White Gaps in Test Scores for Low-Income Students, by Gender



Notes: These figures plot mean math test scores from the National Assessment of Educational Progress for blacks and whites by gender in 2012. The sample consists of all children who are eligible for free or reduced price lunch programs. Panel A presents data for children at age 9, while Panel B presents data for children at age 17. The scores are scaled in standard deviations from the national mean among children in the same cohort. The data used to construct this figure are publicly available and can be downloaded from <https://nces.ed.gov/nationsreportcard/lttdata/>.

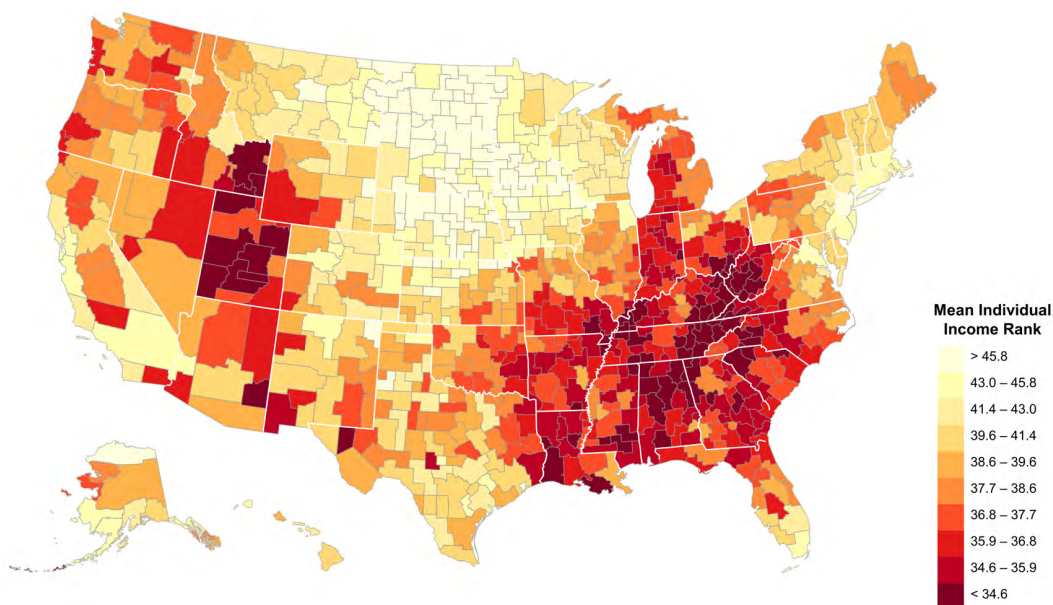
ONLINE APPENDIX FIGURE IX: Geography of Upward Mobility, Mean Household Income Rank for Children with Parents at 25th Percentile



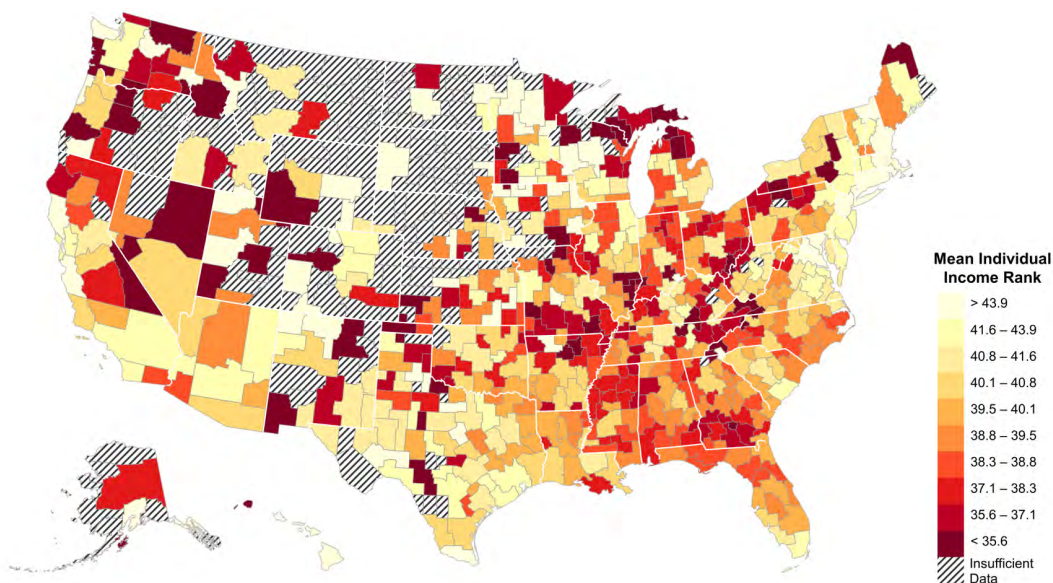
Notes: These figures replicate the results in Figure IX using mean child household income rank for children with parents at the 25th percentile. Panel A shows the predicted household income rank for children of all races, while Panel B and C show the same statistic for white (Panel B) and black children (Panel C). The dollar amounts equivalent to the income ranks at the cutoffs are rounded to the nearest thousand (in 2015 dollars). For further details regarding the construction of the maps, see notes to Figure IX.

ONLINE APPENDIX FIGURE X: Geography of Upward Mobility - Females with Parents at 25th Percentile

A. White Females with Parents at 25th Percentile

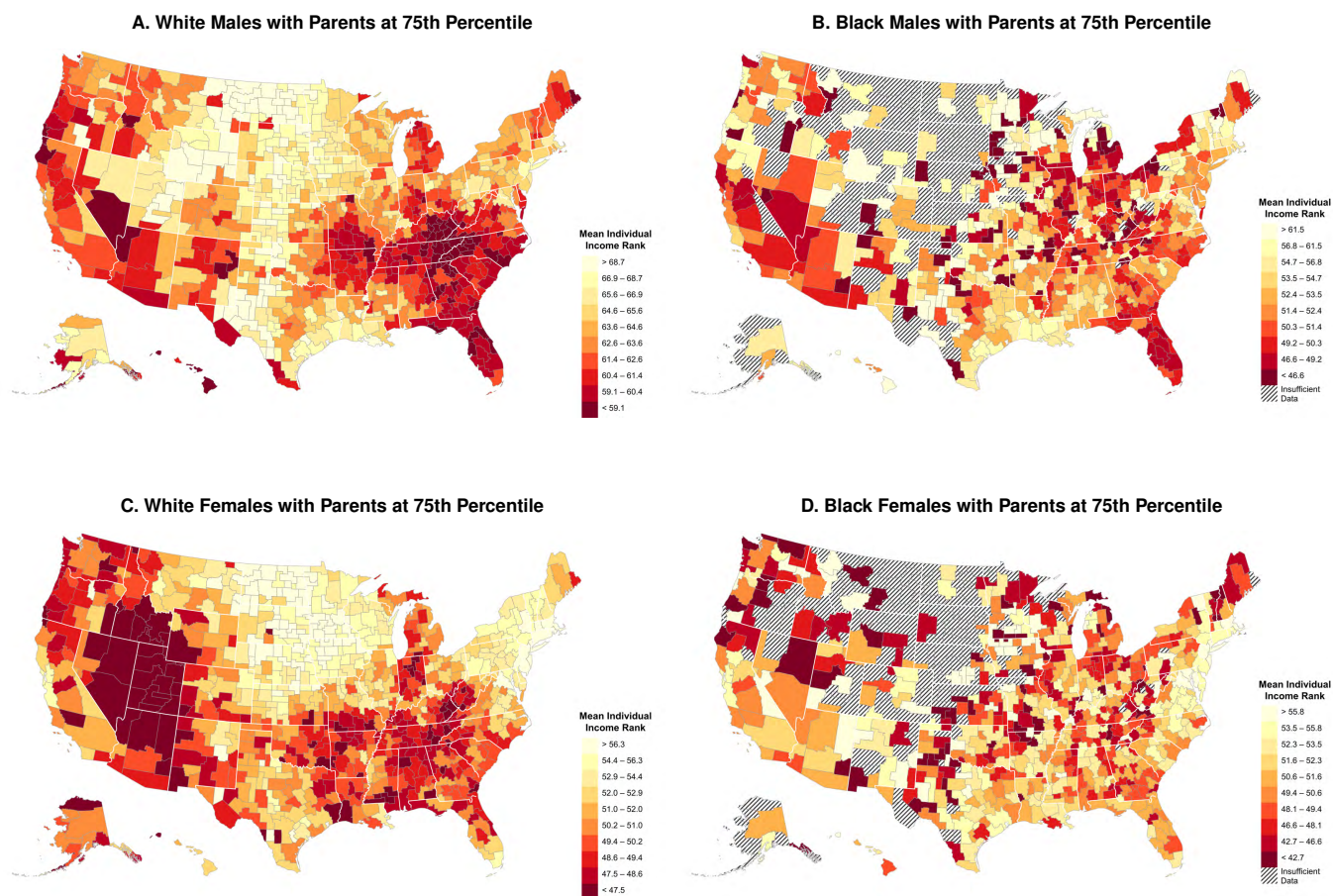


B. Black Females with Parents at 25th Percentile



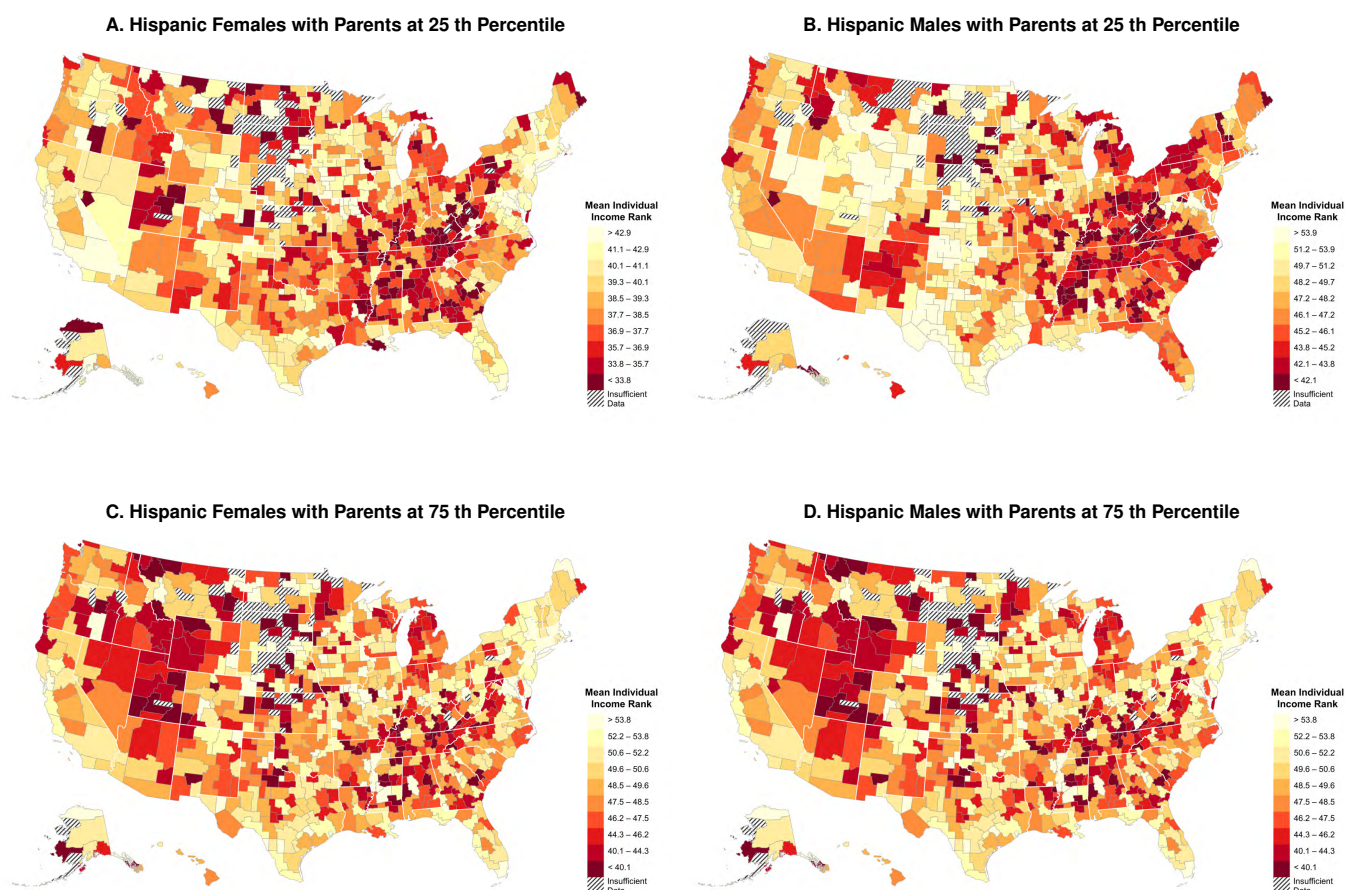
Notes: These figures replicate the results in Figure IX for females. In these figures, the maps are constructed by grouping CZ observations into ten deciles and shading the areas so that lighter colors correspond to higher absolute mobility. Areas with fewer than 20 children in the core sample, for which we have inadequate data to estimate mobility are shaded with the cross-hatch pattern. Panel A shows the mean child individual income rank for white female children, while Panels B shows the same statistic for black females. For further details regarding the construction of the maps, see notes to Figure IX.

ONLINE APPENDIX FIGURE XI: Geography of Upward Mobility - Blacks and Whites with Parents at 75th Percentile



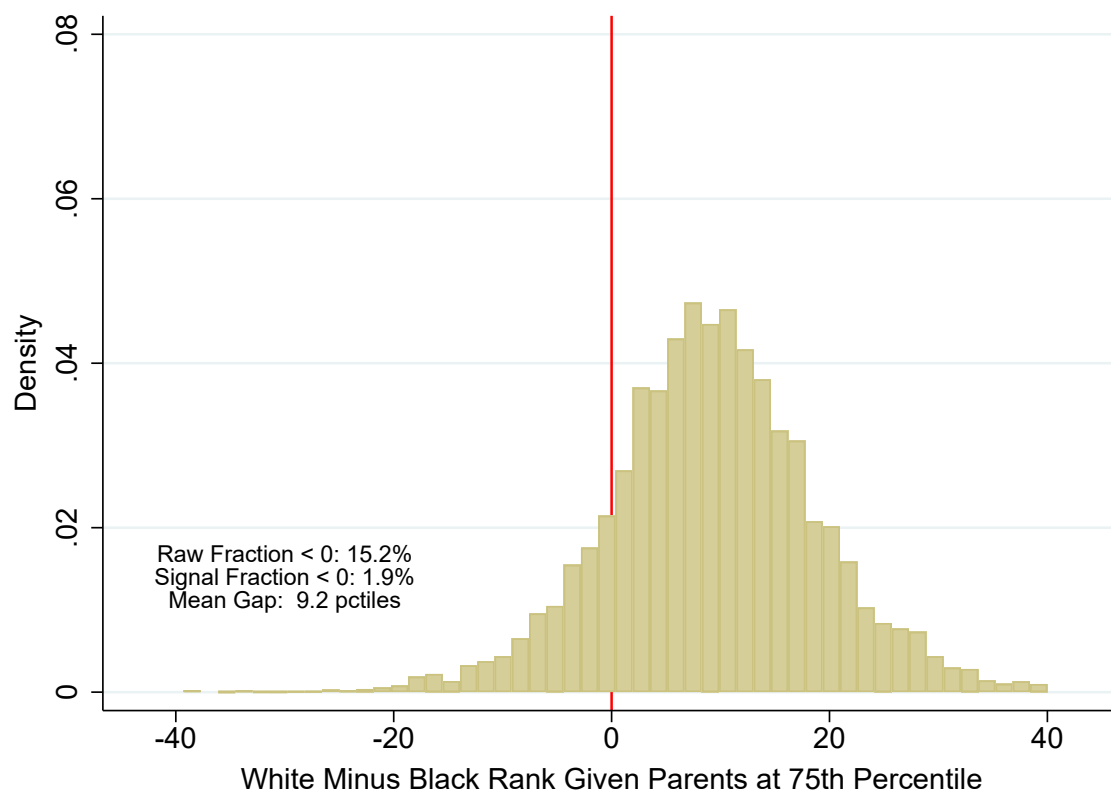
Notes: These figures replicate the results in Figure IX for black and white children with parents at the 75th percentile of the income distribution. In these figures, the maps are constructed by grouping CZ observations into ten deciles and shading the areas so that lighter colors correspond to higher absolute mobility. Areas with fewer than 20 children in the core sample, for which we have inadequate data to estimate mobility are shaded with the cross-hatch pattern. Panel A shows the mean child individual income rank for white male children, while Panels B, C, and D show the same statistic for black males, white females, and black females, respectively. For further details regarding the construction of the maps, see notes to Figure IX.

ONLINE APPENDIX FIGURE XII: Geography of Upward Mobility - Hispanic Children



Notes: These figures reproduce the results in Figure IX for Hispanic children with parents at the 25th and 75th percentile of the income distribution. In these figures, the maps are constructed by grouping CZ observations into ten deciles and shading the areas so that lighter colors correspond to higher absolute mobility. Areas with fewer than 20 children in the core sample, for which we have inadequate data to estimate mobility are shaded with the cross-hatch pattern. Panel A and B show the mean child individual income rank for Hispanic female and male children with parents at the 25th percentile, while Panels C and D show the same statistic for children with parents at the 75th percentile. For further details regarding the construction of the maps, see notes to Figure IX.

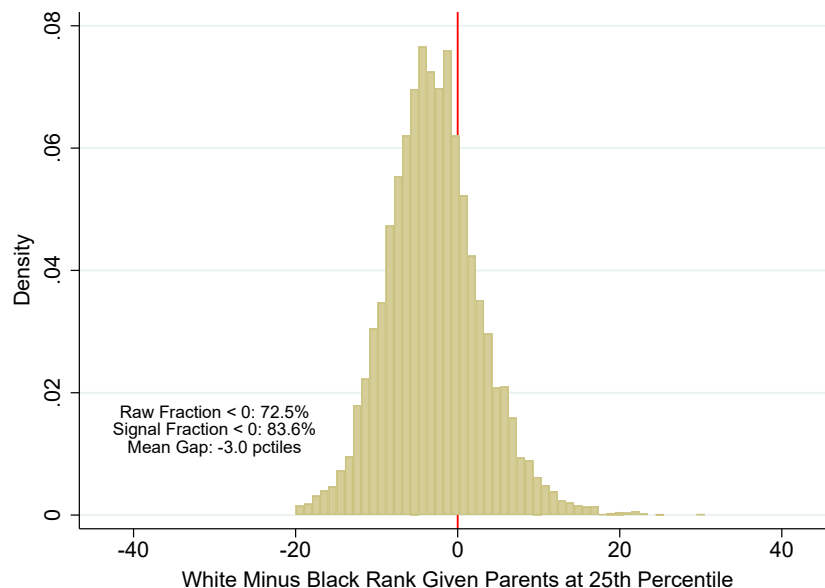
ONLINE APPENDIX FIGURE XIII: Distribution of Black-White Gap in Individual Income Ranks, Males with Parents at 75th Percentile



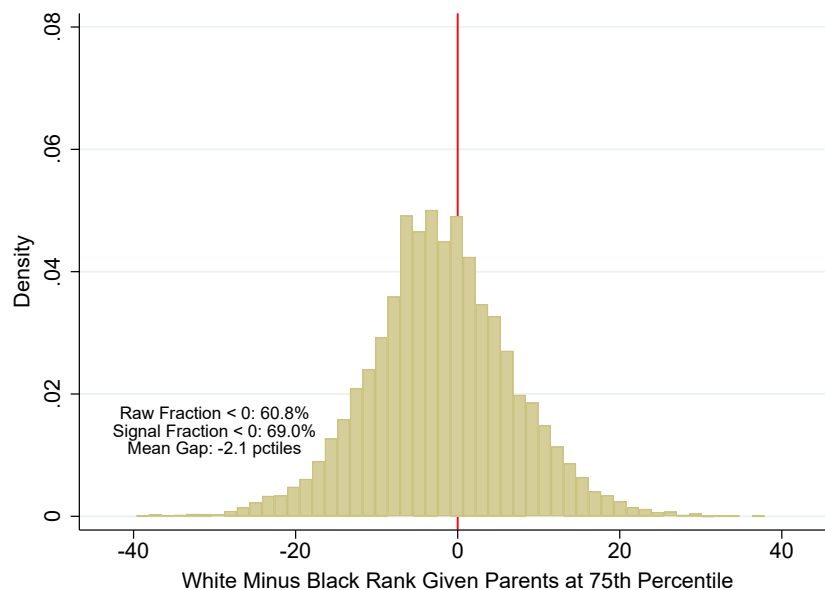
Notes: This figure replicates the results shown in Figure Xa for males with parents at the 75th percentile of the income distribution. For details, see notes to Figure Xa.

ONLINE APPENDIX FIGURE XIV: Distribution of Black-White Gap in Individual Income Ranks, Females

A. Distribution of Female Black-White Gap in Individual Income Ranks, Parents at 25th Percentile



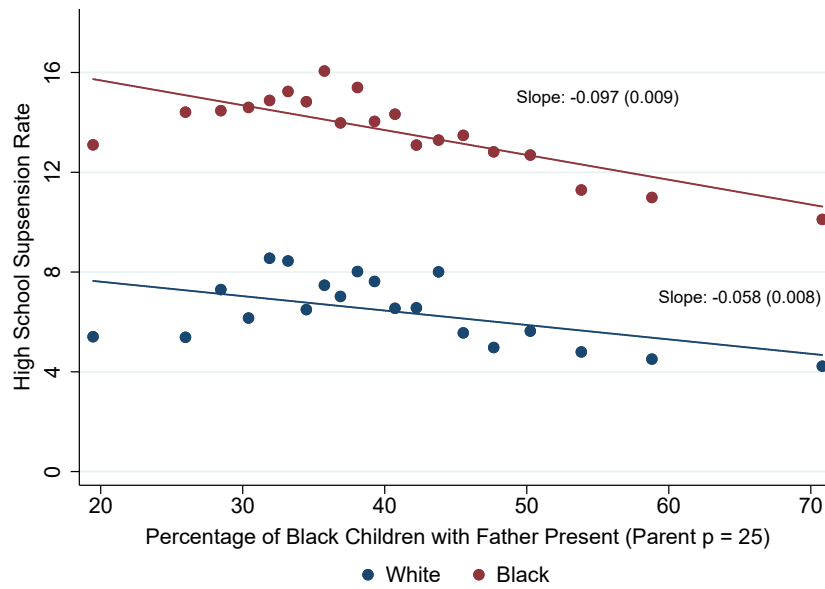
B. Distribution of Female Black-White Gap in Individual Income Ranks, Parents at 75th Percentile



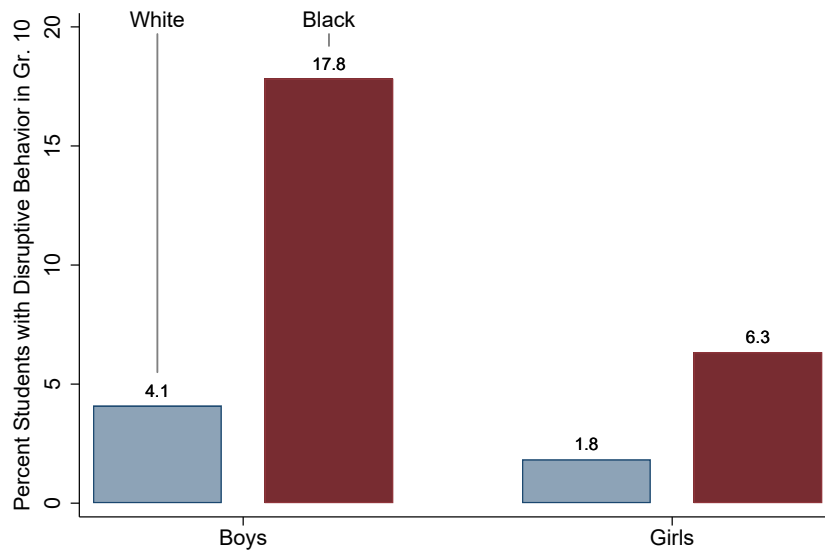
Notes: This figure replicates the results shown in Figure Xa for females with parents at the 25th (Panel A) and 75th (Panel B) percentile of the income distribution. For details, see notes to Figure Xa.

ONLINE APPENDIX FIGURE XV: Suspension Rates and Disruptive Behavior, by Race and Gender

A. High School Suspension Rate for Males vs. Fraction with Fathers in Low-Poverty Areas



B. Disruptive Behavior



Notes: Panel A presents a binned scatter plot of the relationship between the high school suspension rate of black and white male students separately, and the predicted share of black children with parents at the 25th percentile who have a father present in childhood. The sample is restricted to tracts with a poverty rate of 10% or less according to the 2000 decennial Census. The data on suspension rate cover all states except for Indiana, Michigan and Tennessee and are publicly available from the Office of Civil Rights (<https://ocrdata.ed.gov/flex/Reports.aspx?type=school>). Suspension rates are calculated in 2013 and are defined as the number of black students without disabilities who receive at least one out of school suspension during the year, divided by the total number of black students in the school. The best fit line and slope are estimated on the tract level data. Panel B presents the share of low-income students reported as disruptive in class in Grade 10 by race and gender. The share of disruptive students is defined as the share of students described as disruptive in class most of the time or all of the time by their teachers in the first follow-up to the National Educational Longitudinal Study of 1988. NELS data is publicly available and can be downloaded from https://nces.ed.gov/surveys/nels88/data_products.asp.