Racial Gaps in the Early Careers of Two Cohorts of American Men *

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Abstract

This paper studies whether and how early career racial gaps and their underlying forces have changed across two cohorts of young American men (as represented by the NLSY–79 and NLSY–97). Tracking Black and white men from early adulthood into their mid-30s, I first document cross-cohort changes in labor market trajectories over the first eight years after school completion. The upward-sloping employment trajectory is much steeper for the older cohort (NLSY–79) than for the younger cohort (NLSY–97), especially for Black men. I then focus on the 6^{th} through 8^{th} year post-schooling completion, and using a semi-parametric decomposition, I estimate the role of different contributory factors to racial labor market gaps within each cohort, and examine how the patterns have changed across cohorts. I establish three main results. First, measured racial differences in education and skills, especially cognitive skills, explain 30% of the racial labor market gaps in the younger cohort and 60% of the gaps in the older cohort. The explanatory power of education and skills to the racial gaps in the younger cohort is robust to conditioning on family and neighborhood, but in the older cohort, the order of the decomposition matters. Second, while Blacks in the older cohort were later able to close the racial gaps in the school-to-work transition, these gaps continued to have a persistent effects on racial gaps in economic outcomes for the younger cohort. Third, for both cohorts, the explanatory power of childhood neighborhoods, at least at levels observed in the NLSY data, is small or negligible conditional on racial differences in family background and individual skills.

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1 Introduction

Since the Civil Rights Act of 1964, substantial economic progress has been made in closing racial gaps in various aspects of U.S. society (Smith and Welch, 1989). However, more recent evidence casts doubt on whether this relative Black progress is continuing (Council of Economic Advisors, 2016; Wilson and Rodgers, 2016; Daly, Hobijn, and Pedtke, 2017; Bayer and K. Charles, 2018). Recent research shows that substantial and significant racial labor market gaps still persist among the young cohort of Americans (Chetty et al., 2020; Thompson, 2021). In June 2020, demonstrations across the country in support of the Black Lives Matter (BLM) movement has again brought to national attention the long-standing racial disparities in and beyond the labor market.[1]

Despite the growing attention and interest from both the public and academia, there is relatively limited evidence on what underlies the observed racial gaps for young men in today's U.S. labor market and whether and how the underlying forces behind these gaps have evolved across cohorts. In fact, the current narrative of the causes of racial labor market gaps is largely shaped by data over two decades ago and from previous cohorts.[2] Do Black-white differences in education and skills still play an important role in explaining racial gaps for young men in the younger cohort, as in previous cohorts? What about the roles of family background, childhood neighborhood and the school-to-work transition, and have they changed across cohorts? Given that both the characteristics of Americans and the overall structure of the labor market have changed dramatically in the past several decades (Altonji, Bharadwaj, and Lange, 2012; Autor and Dorn, 2013; Castex and Dechter, 2014; Deming, 2017), one cannot simply assume that our knowledge based on previous cohorts applies to today's cohort of young men.

In this paper, I provide some of the first evidence on whether and how the Black-white labor market gaps and the underlying forces have changed across two cohorts of young American

[1]While the demonstrations were in response to police brutality and violence against African Americans and pervasive racism in the criminal justice system, the BLM movement has also brought up public discussions on racial divide in other aspects of the society, such as labor market outcomes and wealth (NPR, 2020; Washington Post, 2020; Financial Times, 2020).

[2]The literature on the potential determinants of racial labor market gaps is enormous. For example, pre-market skills (or human capital) have been shown to be crucial in understanding racial gaps in labor market outcomes (e.g., Neal and Johnson, 1996; Heckman, Stixrud, and Urzúa, 2006; Urzúa, 2008; Lang and Manove, 2011; Thompson, 2021). Family background and parenting style have been long understood as pivotal predictors for children's outcomes, and evidence shows there are important racial differences in how parents raise and educate their children (e.g., Lareau, 1987; McAdoo, 2002; Thompson, 2018). In addition, an important series of studies have documented the important the role of discrimination (e.g., Donohue and Heckman, 1991; Pager, 2003; Charles and Guryan, 2008).

men. This is facilitated by using two similarly constructed samples of the National Longitudinal Survey of Youth, the NLSY–79 and the NLSY–97, which are nationally representative samples of young Americans born in 1957–1964 and 1980–1984, respectively.[3] Tracking the two cohorts of Black and white men from early adulthood to their mid-30s, I first document the Black-white differences in labor and earnings trajectories and how the pattern has changed across cohorts.[4] I find that over the first eight years after the completion of schooling, the racial gap in employment and earnings narrows significantly in the older cohort (NLSY–79) but stays broadly steady in the younger cohort (NLSY–97). In other words, the initial racial labor market gap is much more persistent through the early career years in the younger cohort.

In my main analysis, I conduct a comprehensive analysis of underlying factors behind the racial labor market gaps in the two cohorts by harnessing the richness of individual and family characteristics in the NLSY data and using restricted geocode files to identify childhood neighborhoods. In particular, I examine the explanatory power of three pre-market characteristics—education and skills, family background, and childhood neighborhood—and the school-to-work transition[5] using a semi-parametric decomposition method (DiNardo, Fortin, and Lemieux, 1996). I focus on racial gaps in weeks worked per year and average annual earnings observed over the sixth to eighth years after the young men completed formal schooling, when their labor market outcomes reached a relatively stable stage.

I establish three main empirical results. First, education and skills play a key role in explaining racial labor market gaps in the younger cohort (NLSY–97) as well as in the older cohort (NLSY–79). In the NLSY–97, racial differences in measured education and skills explain about 30% of the racial gaps in employment and earnings. The explanatory power of education and skills is attributable primarily to racial differences in cognitive skills, as measured by the Armed Forces Qualification Test (AFQT) score, rather than to differences in formal schooling or social and non-cognitive skills.[6]

[3]Throughout this paper, I refer to the NLSY–79 as the "older" cohort and the NLSY–97 as the "younger" cohort. Altonji, Bharadwaj, and Lange (2012) is one of the first papers that compare the NLSY–79 and the NLSY–97 cohorts, and their focus is on how the characteristics of young Americans have changed across cohorts. As a recent example, Thompson (2021) combines the two NLSY cohorts with an older cohort (NLS-Young Men), and examines how the racial gaps have evolved from a longer time perspective.

[4]The schooling and work history files are similarly constructed for the NLSY–79 and the NLSY–97 cohorts, facilitating a valid cross-cohort comparison.

[5]To keep the decomposition results comparable between the two cohorts, I mainly follow Altonji, Bharadwaj, and Lange (2012) and include the individual, family, and neighborhood variables that are similarly constructed or can be appropriately concorded. I discuss variable definitions in detail in the next section.

[6]An NAS study on the test's racial fairness concluded that the AFQT score does not systematically underpre-

As a comparison, racial differences in education and skills explain about 60% of the gaps in the older cohort (NLSY–79), which is consistent with existing studies using the NLSY–79 data (Neal and Johnson, 1996; Urzúa, 2008).[7] The cross-cohort change in the explanatory power of education and skills can be largely attributed to falling racial gap in cognitive skills (AFQT score) across cohorts, although the gap in the younger cohort remains quantitatively substantial and statistically significant.

What does the crucial role of racial skill differences imply? The measure of cognitive skills in my data, the AFQT score, is observed at ages 12–18 and can be a function of a series of family investments and neighborhood influences in early childhood years. To shed light on what underlies the racial skill gaps, I estimate the contribution of education and skills after *conditioning on* measured racial differences in family background and childhood neighborhood characteristics.

In the younger cohort (NLSY–97), the explanatory power of education and skills remains quantitatively robust (about 30%) even after conditioning on family and neighborhood characteristics. Conversely, in the older cohort (NLSY–79), the explanatory power of education and skills goes away almost entirely after accounting for racial differences in family and neighborhood characteristics. This suggests that much of the measured racial skill gap in the older cohort can be explained by racial differences measured at the family and neighborhood level, while raising an important question on the origins of the racial skill gaps among young men in today's labor market.[8] Although my paper does not answer this question, my findings reinforce the literature that emphasizes the critical role of skill development (Heckman, Stixrud, and Urzúa, 2006; García, Heckman, and Ziff, 2019; García et al., 2020) under the context of the young cohort of Americans. It is important to continue to focus on institutional and economic barriers to Black men in the skill accumulation process.[9]

dict the job performance of Blacks relative to whites in the military (Wigdor and Green Jr., 1991).

[7] In Neal and Johnson's (1996) influential work, cognitive skills (AFQT score) on their own account for about 60% of the racial wage gap between Black and white men. Urzúa (2008) makes a distinction between measured cognitive skills (AFQT score) and underlying cognitive ability and shows that cognitive ability explains about 40% of the racial gaps in wages and earnings.

[8] It is possible that some of the racial differences in measured cognitive skills in my data could have originally come from Black and white men's earlier childhood exposure to unobserved neighborhood characteristics, such as local school quality. Meanwhile, as emphasized in Cunha et al. (2006), family investments may play a more crucial role than schools in children's skill accumulation process.

[9] For example, more than 60 years after *Brown v. Board of Education*, evidence shows that segregated schools are still preventing many Black children from obtaining education and skills that are crucial for their future success in work and life (Reardon and Owens, 2014; The Atlantic, 2018; New York Times, 2019; Economic Policy Institute, 2020).

Second, although Black men in both NLSY cohorts, compared to their white counterparts, started their careers with a significantly worse condition, this Black disadvantage in the school-to-work transition has a particularly important role in explaining racial gaps in later labor market outcomes for the younger cohort (NLSY–97). Specifically, I measure the school-to-work transition with employment outcomes in the first year post-schooling and local labor market conditions (unemployment rates) upon schooling completion.[10] In the NLSY–97 cohort, racial gap in the school-to-work transition explains up to 30% of the racial labor market gaps measured over the sixth to eighth years post-schooling, after conditioning on racial differences in the pre-market characteristics. This finding is intuitively consistent with the series of studies showing that poor outcomes early in the school-to-work transition have a long-lasting impact on future labor market outcomes (Kahn, 2010; Schwandt and Wachter, 2019).

In contrast to the NLSY–97, the conditional explanatory power of the school-to-work transition on racial gaps in later outcomes is not found in the NLSY–79. What makes the school-to-work transition in the younger cohort distinct from the older cohort? One possible explanation is the Great Recession, which covered a large part of the early career years for young men in the NLSY–97 sample. Failing to make the school-to-work transition during the Great Recession can be more consequential (in terms of affecting future labor market prospects), compared to smaller recessions experienced by young men from the NLSY–79 cohort.

Third, I examine the role of childhood neighborhood characteristics in explaining the observed racial labor market gaps. For this analysis, I mainly focus on the NLSY–97 cohort. This allows me to draw a more direct comparison to the documented neighborhood effects in the recent literature (e.g., Chetty et al., 2020), as Chetty et al.'s sample is from a similar birth cohort, and allows me to incorporate a richer set of neighborhood and family variables. On its own, the set of childhood neighborhood characteristics I observe for the NLSY–97 explains approximately 10%–20% of the racial gaps in employment and earnings.[11] After conditioning on racial differences in education and skills and family background, however, the explanatory power of neighborhood characteristics substantially declines to small or negligible.[12]

My findings do not directly contradict Chetty et al. (2020), as they do not incorporate

[10] Unemployment rates (UR) data are taken from the Local Area Unemployment Statistics (LAUS) program.

[11] The geocode file of NLSY–97 is as detailed as the county level, and I also include some measures of within-county neighborhood quality. The unconditional explanatory power of my neighborhood measures increases up to 24% under a linear decomposition. This is closer to the explanatory power of census tract fixed effects (about 30%) in Chetty et al. (2020), which imposes a linear functional form and looks at income rank as the outcome.

[12] I find a qualitatively similar pattern for the NLSY–79.

direct measures of cognitive skills into their analysis. However, my findings do suggest two possible interpretations of the documented neighborhood effects in Chetty et al. (2020). First, the unconditional explanatory power of neighborhood documented both in the NLSY–97 and in Chetty et al.'s (2020) data may reflect residential sorting of Black and white families into different neighborhoods, as pointed out by Heckman (2018). Second, as I discussed earlier, if there is indeed a true effect of neighborhoods on racial labor market gaps, it is possibly working through the channel of skill accumulation.

Discrimination is an important source of the observed racial gaps in the U.S. labor market (e.g., Donohue and Heckman, 1991; Pager, 2003; Bertrand and Mullainathan, 2004; Charles and Guryan, 2008), and there are multiple channels through which it relates to the factors incorporated in my analysis. First, Black men (and their parents) who anticipate there will be labor market discrimination may underinvest in skill accumulation. Second, racial differences in the school-to-work transition could also be picking up discrimination faced by Black men in their initial labor market experiences. Third, if, due to discrimination, Black and white men are receiving different labor market returns to the same characteristics, then this will be reflected in the residuals of the decomposition.[13]

The remainder of this paper proceeds as follows. Section 2 describes the NLSY datasets and how I create the concordance of variables between the two cohorts. Section 3 presents the early career labor market trajectories for Black and white men in the two NLSY cohorts. It also shows how the racial differences observed in the pre-market characteristics have changed across the two cohorts. Section 4 introduces the semi-parametric decomposition method, which I use to examine the underlying explanatory forces of the observed racial labor market gaps. Section 5 discusses the decomposition results, and Section 6 concludes.

2 Comparing Two Cohorts of Young American Men

This paper examines whether and how racial labor market gaps and their underlying explanatory factors have evolved across cohorts. I mainly rely on the 1979 and 1997 cohorts of the National

[13]The impact of discrimination on racial labor market gaps can go beyond the border of the labor market. For example, racial discrimination in the criminal justice system reduces the labor market prospects of Black men, which could further discourage Black children and Black families from investing in education and skills. Racial discrimination in the housing market and in the education system could limit the opportunities for Black children to live and learn in promising environments and therefore restrict the possibility of narrowing the racial skill gap.

Longitudinal Survey of Youths (NLSY–79 and NLSY–97). With proper sample weights, the NLSY–79 and the NLSY–97 are nationally representative of young Americans born between 1957–1964 and 1980–1984, respectively. In this section, I discuss the advantages of the NLSY datasets and how I construct the samples and variables.

2.1 Data: NLSY–79 and NLSY–97

My analysis uses Black and white men from both the main sample and the minority subsample of the NLSY–79 and the NLSY–97.[14] The NLSY dataset fits the purpose of my analysis in four important ways. First, it includes a monthly diary of school enrollment and a weekly diary of work status, which I use to define the exact time at which a young man completes schooling and to track his employment and earnings outcomes year by year. I define schooling completion following the literature (Light and McGarry, 1998; Neumark, 2002).[15] My main analysis uses a balanced panel of young men who have not been enrolled in school for at least eight years (or 96 months) and track their labor market outcomes through the first eight years post-schooling. As I show below, the work trajectories of both Black and white men in both cohorts reach a relatively steady stage about six to eight years beyond school completion.

Second, the NLSY records rich information on individual, family, and neighborhood characteristics, all of which is critically important for my decomposition analysis. In particular, it includes a measure of cognitive skills (AFQT score) that has been shown by past studies to be a key determinant in understanding racial gaps in the U.S. labor market (Neal and Johnson, 1996).[16] Third, the NLSY follows incarcerated respondents. This is extremely important in

[14] I do not include the economically disadvantaged white subsample or the military subsample of the NLSY–79.

[15] Specifically, I identify the first month when a young man was no longer enrolled in school and define the next 12 months as the first year post-schooling. My findings are robust if I define the first post-schooling year as the first calendar year that a young man is completely out of school. If a young man graduated from high school, worked for a few years, went back to college, and rejoined the workforce later, his post-schooling experiences are defined to only include the post-college years. This definition therefore excludes two kinds of work experiences: 1) part-time jobs while enrolled in school and 2) relatively temporary work spells that are followed by returning back to school (as in the previous example).

[16] An important question related to the AFQT score, just like almost all other psychometric test scores for skills and abilities, is whether the test is biased in favor of one group over another. Since its first introduction by the Department of Defense for screening enlistees and assigning them to different occupations, a key question especially relevant for the purpose of this paper is whether the AFQT score is *racially* biased. In 1991, the National Academy of Sciences (NAS) led a study in the military focusing on the test's racial fairness and concluded that the AFQT score does not systematically underpredict the job performance of Blacks relative to whites (Wigdor and Green Jr., 1991). The NAS study provides the best evidence to date regarding the test's fairness, as it *directly* observes and measures military job performance and links it to the AFQT score, which is hardly available in civilian datasets. Whether the findings of the NAS study can be applied to the civilian population is largely an open question. In the literature, some studies cast doubt on the score's racial fairness (Rodgers and Spriggs,

the context of understanding racial gaps in labor market outcomes, as Black men are overrepresented in the incarcerated population and much of the NLSY–97 cohort has grown up under a historically high incarceration rate.[17] Bayer and Charles (2018) show that ignoring the trend of the ever-increasing prison population leads to an understatement of the racial earnings gap, especially since the late 1970s.

Last, and most importantly, the NLSY–79 and the NLSY–97 surveys are designed and administrated in a similar way that much of the key variables from the two cohorts are comparable either directly or after some concordance, facilitating a valid comparison between the two cohorts. In my main analysis, I use the individual and family variables constructed by Altonji, Bharadwaj, and Lange (2012) and Deming (2017) and create measures of neighborhood characteristics using the restricted-use geocode files.

2.2 Sample Decisions and Variable Definitions

To make sure that the early career trajectories are comparable between the two NLSY cohorts, I construct the samples following two principles. First, the school enrollment diary starts in 1980 for the NLSY–79 cohort and in 1997 for the NLSY–97 cohort. For young men who completed schooling before the enrollment diary started, the exact school exit time cannot be identified. To minimize this issue without losing too much sample size, I therefore exclude NLSY–79 respondents who were older than 18 as of 1980.[18] For both cohorts, I also exclude young men who were already out of school when the enrollment diary started or were still enrolled in school as of the most "recent" wave.[19]

Second, as of the most recent wave of the NLSY–97 cohort in 2015, the respondents were around ages 30–34. I focus my analysis of the NLSY–79 cohort to survey years 1979–1996, so in the most "recent" wave of 1996, the NLSY–79 respondents were in an age range (31–34) close to the NLSY–97 cohort. To keep the restricted samples nationally representative, I apply the custom sample weights created by the Bureau of Labor Statistics.

I construct measures of education and skills and family background following the literature.

1996), while others conclude otherwise (Heckman, 1998).

[17]The incarceration rate has more than tripled since 1980, and criminal justice policies have been shifting toward more punitive treatment, the burden of which falls disproportionately more on Black men (Neal and Rick, 2014; Council of Economic Advisors, 2016).

[18]All NLSY–97 respondents were younger than 18 as of 1997.

[19]In other words, my sample includes young men who completed schooling after the enrollment diary started and before the most "recent" wave.

Specifically, my measures of education and skills include four variables: highest grade completed, AFQT score (as a measure of cognitive skills), non-cognitive test score, and social test score. The AFQT score is measured at different ages for the two NLSY cohorts and for people in the same cohort (ages 15–23 in the NLSY–79 cohort and ages 12–18 in the NLSY–97 cohort). The test format also changed from a paper-based test in the NLSY–79 to a computer-based adaptive test in the NLSY–97. Altonji, Bharadwaj, and Lange (2012) carefully adjust for different test-taking ages and test format changes between the two cohorts, and I use their adjusted AFQT score.

Unlike the AFQT score for cognitive skills, there is no consistent measure of non-cognitive or social skills in the NLSY–79 and NLSY–97 cohorts. Deming (2017) selects survey questions and/or tests from the two cohorts that seem to measure similar skills and creates standardized non-cognitive and social test scores. Without a better way to handle this incompatibility issue, I use the test scores from Deming (2017). It is important to note that my decomposition results are quantitatively robust with or without including the non-cognitive and social test scores.

My set of family background includes three variables constructed by Altonji, Bharadwaj, and Lange (2012): parental income measured at the first wave of each cohort, mother's highest grade completed, and family structure (whether the respondent lives with both parents) during childhood.[20] In some of my empirical analyses, I include two more family variables that are only available in the NLSY–97 data: whether the respondent's mother is a teenage mom and the mother's parenting style (Doepke and Zilibotti, 2017).

I construct measures of childhood neighborhood characteristics using the restricted-use geocode files for the NLSY. For the NLSY–79 cohort, I link county of residence at age 14 with county socioeconomic conditions created from the 1980 Census, and for the NLSY–79 cohort, I link county of residence at age 12 with the 2000 Census. The socioeconomic variables include county population, median household income, poverty rate, and the share of men with a college education.[21] I also include the same variables but at the state level. To capture some of the within-county

[20]Family structure is measured at age 14 for the NLSY–79 cohort and at the first wave (ages 12–16) for the NLSY–97 cohort.

[21]Residence at age 14 is reported for the NLSY–79, and residence at age 12 is reported for the NLSY–97. This difference will not create major incomparability between the two cohorts (for the purpose of constructing neighborhood measures) if residence does not change much from age 12 to 14. In the geocode files of the NLSY–97, residence at the time of the first survey (in 1997, when the respondents were 12–16) is also reported. As suggestive evidence, I find that the state of residence does not change for 96% of the NLSY–97 respondents from age 12 to the time of the first survey, and county of residence does not change for 93% of the NLSY–97 respondents over the same time period.

variations in neighborhood quality, I further account for whether childhood residence is in a central city, whether it is in a metropolitan statistical area (MSA), and whether it is in an urban or rural area.[22] In some cases, I also include neighborhood variables only available in the NLSY–97 data: homeownership status at the first survey and a set of neighborhood quality measures at the county and commuting zone levels created by Chetty and Hendren (2018b).[23]

The final sample includes 444 white men and 271 Black men from the NLSY–79 cohort and 825 white men and 396 Black men from the NLSY–97 cohort. These young men have completed schooling for at least eight full years and have a complete list of the aforementioned variables of education and skills, family background, and childhood neighborhood characteristics.

3 Documenting Cross-Cohort Changes in Racial Gaps

In this section I first show how the racial gaps in early career trajectories have evolved across the two NLSY cohorts, where I focus on employment and earnings outcomes in the first eight years after a young man completed schooling. I then provide descriptive evidence on how the racial gaps in pre-market characteristics have changed across cohorts.

3.1 Racial Gaps in Early Career Trajectories

Table 1 summarizes the early career outcomes in two periods: the school-to-work transition stage, defined as the first year post-schooling, and the later stage, defined as the sixth to eighth years. I specifically look at the sixth to eighth years because this is when employment and earnings outcomes of young men reached a relatively stable stage. I also summarize the *growth* in the outcomes from the first year to the sixth to eighth years.[24]

In both cohorts, Black men fell substantially behind their white counterparts in the transition stage along multiple margins of employment and earnings. In the NLSY–79 cohort, it took Black men 30 more weeks to get their first job, and in the NLSY–97 cohort, it took them 22 more weeks. The decrease across cohorts in the racial gap is quantitatively large although statistically

[22] This residence type information is measured at the first wave (ages 14–17) for the NLSY–79 cohort and at age 12 for the NLSY–97 cohort.

[23] Chetty and Hendren (2018b) create neighborhood quality measures separately for men and women from high- and low-income families. I use the two measures created for men from high-income families and men from low-income families.

[24] Annual earnings are adjusted to 2013 dollars. I use inverse hyperbolic sine to allow for zeroes. For simplicity, I use the word "log" instead of inverse hyperbolic sine throughout the paper.

insignificant partly due to the sample size. In the first year post-schooling of both cohorts, Black men were less likely than white men to have any job, to work for half a year ($\geq$ 26 weeks), or to work for a full year ($\geq$ 50 weeks). In the NLSY–79 cohort, Black men worked 13 fewer weeks in the first year, and they worked 9 fewer weeks in the NLSY–97 cohort. The racial gaps in all of these employment outcomes have fallen across cohorts, and some of the declines (any employment, full-year employment) can be statistically distinguished from zero. The racial gap in annual earnings are large and significant in both cohorts, but the change from the NLSY–79 cohort to the NLSY–97 cohort is minimal. If one only looks at the racial gaps at the transition stage, a likely and natural conclusion is that the relative position of Black men has actually improved across cohorts, especially in employment outcomes.

The longitudinal structure of the NLSY data allows me to track Black and white men through their early career years and ask: Have these racial gaps converged or persisted through the sixth to eighth years, and how have the trends changed across cohorts? For Black and white men in both cohorts, weeks worked per year and annual earnings increased from the transition stage to the sixth to eighth years, with the increase greater for Black men (i.e., they caught up to white men). As a result, the racial gaps in weeks worked and earnings diminished over the first eight years post-schooling. In the NLSY–79 cohort, the racial gap in weeks worked per year fell from 13 weeks in the first year to 6 weeks, on average, in the sixth to eighth years. In the NLSY–97 cohort, the racial gap in weeks worked per year fell from 9 weeks to 7 weeks. The convergence in weeks worked between Black and white men is smaller in the younger cohort than in the older cohort (by about 5 weeks per year), and the cross-cohort difference is statistically significant. The convergence in earnings is also smaller in the younger cohort but is insignificant from zero.

For a large share of young men in the NLSY–97 sample, their early career years overlapped with the Great Recession, as shown in Figure 1. Because less advantaged groups have been shown to experience more economic losses during economic downturns than their white counterparts (e.g., Schwandt and Wachter, 2019), it is plausible that the Great Recession suppressed the potential for this younger cohort of Black men to catch up in labor market outcomes in their first few years out of school.

In addition to the summary statistics, Figures 2–4 directly plot the trajectories of various employment and earnings outcomes through the first eight complete years post-schooling, allowing a visual examination of how the *shapes* of employment and earnings trajectories have changed between the two cohorts. In the NLSY–79 cohort, young men of both races experienced clear upward-sloping career trajectories, as their employment and earnings outcomes gradually improved, especially in the first four to five years after completing schooling. Importantly, the upward-sloping trend is stronger for Black men, generating the catching-up shown in Table 1. In the NLSY–97 cohort, however, the employment and earnings outcomes of both races either stayed largely stable through the first eight years post-schooling or experienced flatter upward-sloping trajectories than young men in the NLSY–79 cohort. This latter evidence is consistent with the anecdotal observation that the younger cohort of Americans have struggled to gain a foothold in the labor market and to climb up the career ladder (The Atlantic, 2015; Forbes, 2016).

Another important pattern from Figures 2–4 is that the employment and earnings trajectories had more fluctuations and steeper growth in the first few years and started to enter a relatively stable stage around the fourth and fifth years. This is consistent with historical evidence that most job mobility and wage growth happens in the first few years of one's career (e.g. Topel and Ward, 1992). In the decomposition analysis in the next section, I therefore primarily focus on racial gaps in employment and earnings outcomes measured over the sixth to eighth years post-schooling.

3.2 Racial Gaps in Pre-Market Factors: Education and Skills, Family Background, and Childhood Neighborhood

To examine how much of the observed racial gaps in labor market outcomes can be explained by underlying characteristics, it is important to first understand whether there are racial gaps in the underlying characteristics and whether and how the gaps have changed across cohorts. Table 2 compares Black and white men in each cohort along the series of pre-market characteristics (education and skills, family background, and childhood neighborhood) discussed in the previous section and tests whether the racial gap in each factor has changed significantly across cohorts.[25]

Among the four variables measuring education and skills, the racial gaps in highest grade completed and AFQT score percentile are statistically significant in both cohorts, and the racial

[25] Altonji, Bharadwaj, and Lange (2012) create an index of skills for young Americans of the two NLSY cohorts and show that the racial skill gap has fallen, on average, between Black and white men from the NLSY–79 cohort to the NLSY–97 cohort. The authors construct the skill index based on a set of skill measures (including schooling, AFQT score, parental education, family structure, and school-to-work transition measures) and its relationship with wages in the NLSY–79. The authors also show how the skill distribution has changed across cohorts.

gap in social test score is statistically significant only in the NLSY–97 cohort. From the NLSY–79 cohort to the NLSY–97 cohort, the starkest change is a decrease in the racial gap in AFQT score. On average, the racial AFQT score gap has fallen significantly, by more than 10 percentiles. This observation is consistent Altonji, Bharadwaj, and Lange (2012), who find that the skill-related characteristics of young Americans have changed dramatically between the two NLSY cohorts and that the cross-cohort change is largely driven by AFQT score. The racial gap in social test score has increased significantly, but the magnitude of change is arguably modest (about 0.35 standard deviations). The racial gap increases slightly in highest grade completed and decreases slightly in non-cognitive test score. Both changes are indistinguishable from zero.

For family background characteristics, the racial gaps in all three variables are statistically significant within each NLSY cohort. Comparing across cohorts, the racial gap in parental income has increased significantly, while the racial gap in mother's education has fallen (but the change is not statistically significant). Young men of both races are less likely to grow up in a two-parent family in the NLSY–97 cohort than in the NLSY–79 cohort, but the racial gap in childhood family structure stays almost unchanged between the two cohorts.

In both cohorts, Black men tend to grow up in counties and states with a larger population, lower median household income, higher poverty rate, and lower share of men with a college education. Some of these racial gaps in neighborhood socioeconomic conditions appear to have fallen from the NLSY–79 cohort to the NLSY–97 cohort (such as county median household income and poverty rate). During their childhood, Black men are more likely to live in central cities and white men are likely to live in suburban areas (MSA, non-central city, urban areas). This racial difference seems to have also decreased across cohorts.

4 Decomposition Method

To assess how the different underlying factors contribute to the documented racial employment and earnings gaps, I rely on the semi-parametric decomposition method introduced by DiNardo, Fortin, and Lemieux (1996, hereafter DFL).[26] This method relaxes the parametric functional forms that the classical Oaxaca-Blinder decomposition (or other decompositions based on linear

[26] Altonji, Bharadwaj, and Lange (2012) apply the DFL method to study how the characteristics of young Americans have changed from the NLSY–79 to the NLSY–97 and what it means for the labor market prospects of the NLSY–97.

regressions, such as Gelbach (2016)) imposes on the relationship between labor market outcomes (such as employment and earnings) and individual, family, and neighborhood characteristics.[27]

In this section, I briefly describe the DFL method under the specific context of understanding racial labor market gaps. I leave the methodological details and a discussion on how DFL estimates relate to other estimates in the literature to the Appendix B.

In a nutshell, the DFL decomposition constructs the counterfactual distribution of labor market outcomes that can be used to answer questions such as "What earnings would white men have had if they had the same underlying characteristics (such as education and skills, family background, childhood neighborhood, or the school-to-work transition) as Black men in the same cohort?" The difference between the actual and counterfactual earnings for white men can then be seen as the contribution of Black-white differences in the underlying characteristics to the Black-white earnings gap.[28]

Two features of the DFL decomposition are especially relevant for this paper. First, when evaluating the contribution of a *subset* of the underlying characteristics, the DFL estimates depend on the specific sequential ordering by which different characteristics are added. The contribution of later-added characteristics is estimated after *conditioning on* racial differences in earlier-added characteristics.[29] Under a similar context, Altonji, Bharadwaj, and Lange (2012) argue that a natural ordering is the one that follows the *timing* of variables.

In my empirical analysis, I explore different orderings as in a *permutation* exercise. Across all orderings, I always keep the school-to-work transition as the last component after all "pre-market" factors (education and skills, family background, childhood neighborhood), because one's transition performance is presumably an outcome of "pre-market" factors. Otherwise, I

[27]Some influential studies that focus on understanding labor market racial gaps have relied on regression-based estimates, which impose strong assumptions on parametric (mostly linear) functional forms (Neal and Johnson, 1996; Chetty et al., 2020). There is evidence showing that some of the parametric assumptions widely imposed in classical regression specifications are not supported by the data (Heckman, Stixrud, and Urzúa, 2006). Under the context of racial wealth gaps, Barsky et al. (2002) show that the classical Oaxaca-Blinder decomposition (Blinder, 1973; Oaxaca, 1973), which imposes strong functional form assumptions, results in misleading conclusions regarding the explanatory power of racial gaps in earnings on the racial wealth gaps.

[28]The DFL method constructs the counterfactual outcomes for white men by reweighting the white men sample to match the Black men sample in one or more underlying characteristics. See Appendix B for details on the reweighting process.

[29]Intuitively, this process is the same as first residualize racial differences in later-added characteristics with racial differences in earlier-added characteristics. If racial differences in the later-added characteristics can be fully (or more than fully) accounted for by racial differences in the earlier-added characteristics, the estimated contribution of later-added characteristics could be close to zero (or negative). In practice, it is not uncommon for DFL decomposition to produce estimates with a negative sign (e.g., DiNardo, Fortin, and Lemieux, 1996; Altonji, Bharadwaj, and Lange, 2012).

hold no prior as to where the "pre-market" factors should be in the sequence relative to each other.

Although I hold no prior on the causal relationships between the "pre-market" factors and the DFL method is not designed to address causality questions, comparing DFL decomposition results across different sequential orderings will help us understand the potential *mechanisms*. For example, when childhood neighborhood is added later than family background and education and skills in the sequence, the contribution of neighborhood is estimated after conditioning on measured racial differences in family and individual characteristics. A general question raised in the literature about the documented neighborhood effect in Chetty et al. (2020) is how much of it reflects the residential sorting of Black and white families and individuals across different neighborhoods (Heckman, 2018). The sequential decomposition results will shed light on this question.[30]

Second, the DFL decomposition focuses on the contributions of Black-white differences in observed characteristics (also known as "quantities"), rather than Black-white differences in *returns* (also known as "prices") paid to these characteristics. If Black men receive lower labor market returns (such as less working time and/or lower wage rates) to the same characteristics, this dimension of racial differences will be left in the residuals of DFL decomposition.[31]

5 Decomposition Results

The DFL decomposition shows how much of the racial employment and earnings gaps, measured at the sixth to eighth years, can be explained by racial differences in quantities of underlying characteristics. I perform the decomposition separately for the two NLSY cohorts and focus on three pre-market characteristics—education and skills, family background, and childhood neighborhood—and the school-to-work transition.[32] I establish three main findings, which I

[30]In a related literature, a series of papers have estimated the causal effect neighborhoods and find positive returns to growing up in "good" neighborhoods (Chetty, Hendren, and Katz, 2016; Chyn, 2018; Chetty and Hendren, 2018a). The DFL method provides complementary results to the casual estimates, by showing what the overall explanatory power of racial differences in the "quantities" of neighborhood characteristics could be.

[31]It might be of particular interest to further decompose the residuals to see, for example, the specific contribution of racial differences in skill prices. Doing this requires imposing additional structure and assumptions on the residuals and is beyond the scope of this paper. One example is Firpo, Fortin, and Lemieux (2018), who proposes a decomposition method based on re-centered influence function regressions. Thompson (2021) examines the contributions of changing skill prices to changing racial gaps using linear regressions.

[32]A common practice in estimating wage or earnings equations is to control for work experience, which is (in many cases) approximated by age or potential experience. I do not include experience in my decomposition (or adjust labor market outcomes by experience) for three reasons. First, work experience itself is a potential

detail in the following sections.

5.1 Central Role of Education and Skills

My first finding concerns the role of education and skills accumulated prior to labor market entry in explaining racial gaps in employment and earnings. I start by presenting result for the NLSY–97 cohort, as summarized in Table 3. The three panels each feature a DFL decomposition that includes the same three sets of pre-market factors but with different sequential orderings. For example, in the decomposition featured in the top panel of Table 3, education and skills are added first in the sequence, family background characteristics are added second, and childhood neighborhood characteristics are added last. Within each panel, I first present the racial gap in employment (average weeks worked per year) and earnings (log of average annual earnings including years of zeroes), and then I present the share of the gap that can be explained by specific factors. The last column presents the share of the racial gap that is left unexplained and is in the residuals.[33]

Racial differences in education and skills explain about 30% of the racial labor employment and earnings gaps in the NLSY–97. This explanatory power of education and skills is quantitatively robust across different sequential orderings. In the top panel where education and skills are added first, they explain 27% of the racial employment gap and 30% of the racial earnings gap. In the middle panel where the contributions of education and skills are estimated conditioning on measured racial differences in family characteristics, the share of the racial employment and earnings gaps explained by education and skills barely changes to 27% (for employment) and 29% (for earnings). In the bottom panel where the contributions of education and skills are estimated further conditioning on childhood neighborhood characteristics, the share of the racial gaps explained by education and skills again stays largely stable and changes to 24% (for employment) and 33% (earnings).

outcome of the pre-market characteristics that my decomposition focuses on. Second, my measure of the school-to-work transition can be seen as a measure of labor market experience, but in one's very first-year after schooling completion. Compared to total *accumulated* work experience, the transition measure is arguably more exogenous to the labor market outcomes measured over the sixth to eighth years post-schooling. Third, my NLSY samples include men who have completed schooling for at least eight years (i.e. have potential experience for at least eight years). This already accounts for some of racial differences in potential experience. If experience still matters in explaining racial labor market gaps *conditioning on* the pre-market characteristics and the school-to-work transition, its contribution will be captured in the residuals of my decomposition.

[33] I leave the discussion of the school-to-work transition to the next section. In Tables 3–5, the contribution of the transition is included in the residuals.

I bootstrap the decomposition process 5,000 times to construct p-values and standard errors. In Appendix Table A.1, I show that the racial labor market gaps explained by education and skills are statistically significant at the 5% level, for both employment and earnings outcomes and across all three sequential orderings.

Given the quantitatively large and robust effect of education and skills, a natural question is whether a specific skill measure has driven this result. Recall that my set of skill measures includes highest grade completed, measured cognitive skills (AFQT score), and measured non-cognitive and social skills. Although it is difficult to disentangle the effects of different skill measures since they can be endogenous to each other, I can explore, in a descriptive sense, which specific skill measure has the dominant explanatory power.[34]

Table 4 contrasts the decomposition results when only the highest grade completed in the set of education and skills (top panel) is included with the results where only cognitive skills (AFQT score) in the set of education and skills (bottom panel) are included.[35] Each panel of Table 4 presents the decomposition results in a similar structure as in Table 3. Comparing between the two panels, the explanatory power of education and skills is attributable primarily to measured cognitive skills (AFQT score) rather than to formal schooling (highest grade completed). The racial gap in highest grade completed alone accounts for 12%–14% of the racial employment and earnings gaps, and its explanatory power decreases to 1%–3% after conditioning on racial differences in family background and childhood neighborhood characteristics.

In stark contrast, the racial gap in measured cognitive skills alone explains about 30% of the racial labor market gaps, and this explanatory power stays largely stable after conditioning on racial differences in family and neighborhood characteristics. The share accounted for by measured cognitive skills is very close to the share accounted for by the full set of education and skills, as shown in Table 3. The dominant explanatory power of AFQT score also highlights the necessity of including some appropriately constructed measure of cognitive skills when studying racial gaps, which is seldom available in "big data," such as administrative tax records.

After establishing the results for the younger cohort, I now show whether and how the explanatory power of education and skills has changed across cohorts. Table 5 presents the

[34] In a structural model, Urzúa (2008) emphasizes the key insight that observed (AFQT) test scores are a function of both underlying (cognitive) ability and other characteristics, including family background characteristics (such as parental income). The author shows that cognitive skills can grow as education attainment increases and people can make endogenous schooling decisions based on their underlying cognitive and non-cognitive abilities.

[35] The results shown here barely change when I add non-cognitive and social scores.

decomposition results for the NLSY–79. Neal and Johnson (1996) show that AFQT score (in a quadratic function) *alone* accounts for about 60% of the wage gap between Black and white men in the NLSY–79. Consistent with their findings, the top panel of Table 5 shows that racial differences in education and skills *alone* explain 64% of the racial employment gap and 67% of the racial earnings gap in the NLSY–79 sample.

Regarding the role of education and skills, there are two main changes between the two NLSY cohorts. First, the absolute explanatory power of education and skills, when estimated *unconditionally*, is higher in the older cohort (60%) than in the younger cohort (30%). As discussed earlier in Table 2, the racial gap in measured cognitive skills (AFQT score) fell substantially and statistically significantly from the NLSY–79 cohort to the NLSY–97 cohort. If the returns to cognitive skills were to have stayed stable across cohorts, a smaller racial gap in cognitive skills would lead to a lower explanatory power of education and skills in the younger cohort. In contrast, recall that in Table 2, the racial gap *increased* insignificantly for highest grade completed and significantly for social test score. Because the explanatory power of education and skills is primarily driven by AFQT score, rather than by highest grade completed or social test score, the falling racial gap in AFQT score is playing the dominant role.[36]

Second, in the younger cohort (NLSY–97), the explanatory power of education and skills is robust across different sequential orderings, while in the older cohort (NLSY–79), the explanatory power decreases substantially after accounting for racial differences in family background and goes entirely away after further accounting for racial differences in childhood neighborhood characteristics. For the NLSY–79 cohort, bootstrap results in Appendix Table A.2 show that the explanatory power of education and skills is significant at the 5% level when estimated unconditionally and becomes indistinguishable from zero after conditioning on family and neighborhood characteristics.

Why is the estimated contribution of education and skills robust across orderings in the NLSY–97, but not in the NLSY–79? In the DFL decomposition, the contribution of later-added

[36]If labor market returns to education and skills were to decrease across cohorts, the explanatory power of education and skills would also decrease (assuming racial differences in education and skills have remained unchanged). However, existing evidence on how returns to education and skills have changed in the U.S. labor market is mixed and still preliminary. Castex and Dechter (2014) find that the returns to education have increased and the returns to cognitive skills have decreased from the NLSY–79 cohort to the NLSY–97 cohort. Deming (2017) further shows that the returns to non-cognitive skills and social skills have increased between the two cohorts. That said, Hellerstein, Luo, and Urzúa (2019) show that the former two studies rely on a strong assumption of constant skill prices and the assumption does not seem to hold in the NLSY–97 cohort. When relaxing this assumption, there is no conclusive evidence on a cross-cohort decline in the returns to cognitive skills.

characteristics are estimated conditioning on racial differences in earlier-added characteristics. In the NLSY–79 cohort, an important share of the observed racial gap in education and skills can be accounted for by measured racial differences in family background, which explains why the estimated contribution of education and skills decline by more than half (from 64% to 30% for employment, from 67% to 17% for earnings) when conditioning on family background (as shown in the top and middle panels of Table 5). Similarly, the observed racial gap in education and skills in the NLSY–79 can be *more than fully* accounted for by the measured racial differences in family and neighborhood characteristics together, which makes the estimated contribution of education and skills (conditioning on both family and neighborhood) further declines to negative (as shown in bottom panel of Table 5).

In contrast, in the NLSY–97 cohort, much of the observed racial skill gap cannot be accounted for by racial differences in family and neighborhood characteristics, at least as can be measured in the NLSY data. The estimated contribution of education and skills is therefore extremely stable no matter which ordering is used, as shown in Table 3. This leads to a further question of where the racial skill gap in the younger cohort originates.

To understand the origins of the observed racial skill gap, it is important to emphasize that the skill measures themselves can be seen as an outcome. For example, cognitive skills (AFQT score) in my data are measured when respondents were ages 12–18 and could be a function of a series of family investments, school influences, and/or neighborhood impacts that happened in early childhood years.[37] Identifying the specific mechanisms behind the racial skill differences in the younger cohort is beyond the scope of this paper, but existing studies can shed light on what the potential mechanisms *could* be.

For example, using a linear regression, Neal and Johnson (1996) show that young men in the NLSY–79 who have high AFQT scores are from a more advantageous background (e.g., more highly educated parents, reading materials at home) and a better school environment

[37] The AFQT score is measured at ages 15–18 in my final sample of the NLSY–79 cohort and ages 12–18 in the NLSY–97 cohort. Note that I use the score constructed by Altonji, Bharadwaj, and Lange (2012), which carefully concords the two cohorts to make the AFQT scores comparable. According to Deming (2017), the non-cognitive score is constructed from two tests (one conducted at ages 14–17 and one at ages 15–18) in the NLSY–79 cohort and is constructed from two sets of questions (one asked at ages 17–21 and one at ages 23–27) in the NLSY–97 cohort. The social score is constructed from two sets of questions (one aims to measure sociability in high school, and one aims to measure sociability at age 6 and as an adult) in the NLSY–79 cohort and is constructed from a set of questions asked at ages 23–27 in the NLSY–97 cohort. As discussed earlier, there is no evidence that the non-cognitive and social scores are directly comparable between the two NLSY cohorts. The findings in this paper are quantitatively robust when excluding non-cognitive and social scores from the analysis.

(e.g., lower student-to-teacher ratio, lower student dropout rate). In a cohort close in age to the NLSY–97, Chetty et al. (2020) show descriptively that low-poverty neighborhoods (census tracts) with low levels of racial bias among whites and high rates of father presence among Blacks tend to have smaller racial income gaps. Considering the relative role of families and schools (or neighborhoods) in the skill formation of children, past studies have established that family investments play a much more crucial role than school and neighborhood influences (Cunha et al., 2006). On top of the roles that family, school, and neighborhood play, pervasive racial discrimination against Black men can also affect the skill formation process. For example, Black families and children anticipating future discrimination in the labor market may choose to underinvest in education and skills.

5.2 Role of the School-to-Work Transition

My second finding focuses on the role of the school-to-work transition in explaining racial gaps in future labor market outcomes. As shown in Table 1, Black men in both cohorts had worse outcomes than their white counterparts in various labor market dimensions in their very first year post-schooling. It has been widely documented in the literature that the school-to-work transition has a long-lasting impact on future labor market outcomes (Neumark, 2002; Kahn, 2010), especially for minority and economically disadvantaged groups (Schwandt and Wachter, 2019).[38] If Black disadvantage caused by the school-to-work transition persists through early career years, it may help explain some of the racial labor market gaps observed in the sixth to eighth years post-schooling, even after conditioning on racial differences in the pre-market characteristics.

Figures 2–4 reveals some suggestive patterns. In the NLSY–79 cohort, the Black-white gap in the transition stage (defined as the first year post-schooling) shows some convergence over the following four to five years, especially in employment outcomes. In the NLSY–97 cohort, there was much less convergence, and the initial racial gaps either largely persisted or grew over the early career years. Although this is not a causal estimate, it does suggest that the persistent impact of the school-to-work transition seems to be especially relevant for the NLSY–97 cohort.

In the decomposition analysis, I try two different measures of the school-to-work transition.

[38] Rinz (2019) shows that exposure to the Great Recession has cost Black workers 1.33 years of their average earnings and has cost white workers 0.94 years of their average earnings. But the estimates are based on all workers, not new workers who just entered the labor market.

The first measure is a flexible function of weeks worked in the first year post-schooling.[39] The second measure uses the geocode files to link a young man's state of residence in the year that he completed schooling (and entered the labor market) with state average unemployment rates from LAUS. This provides a different and presumably more exogenous measure of one's school-to-work transition status. For the younger cohort, when LAUS has more detailed data at the *county* level, I also construct unemployment rates at entry county-year as another measure of transition.[40]

As discussed earlier, I always estimate the explanatory power of racial differences in the school-to-work transition *conditioning on* measured racial differences in education and skills, family background, and childhood neighborhood characteristics. This is because the school-to-work transition measures I use are likely an outcome of the pre-market characteristics.

Table 6 presents the estimated explanatory power of the school-to-work transition separately for the NLSY–97 (top panel) and the NLSY–79 (bottom panel). Within each panel, column (1) shows the racial gap in employment and earnings, column (2) shows the share of the gap explained by the pre-market factors (education and skills, family background, childhood neighborhood) together, and column (3) shows the share of the gap that can be explained by the racial differences in weeks worked in the first year post-schooling, conditioning on racial differences in the pre-market characteristics. Column (4) further adds unemployment rates at entry state-year to the transition measure (on top of weeks worked in the first year post-schooling), and presents the share of the racial gap that can be explained *in addition to* the number presented in column (3). Similarly, column (5) adds unemployment rates at entry *county*-year on top of column (3), and presents the share of the racial gap that can be explained *in addition to* column (3).

In the younger cohort (NLSY–97), when the school-to-work transition is measured by weeks worked in the first year post-schooling (top panel column (3)), it accounts for about 13% of the racial employment and earnings gaps, after conditioning on racial differences in the pre-market characteristics. When the transition is measured by unemployment rates at entry county-year *together with* weeks worked in the first year (top panel column (5)), it accounts for more than 30% of the racial gaps in employment and earnings (13% + 18% = 31% for employment, 13% + 21% = 34% for earnings), after conditioning on the pre-market factors. Out of this

[39] I include a series of indicator variables for the number of weeks worked in the first year post-schooling: 1–9 weeks, 10–19 weeks, ..., 40–49 weeks, and 50 weeks or more.

[40] County-level unemployment rate data in LAUS go back to the year 1990 and are unavailable for most of the NLSY–79 sample years.

explanatory power of transition, more than half comes from racial differences in the exposure to different county unemployment rates upon schooling completion.[41] Using state unemployment rates (top panel column (4)), which is a less accurate measure of local labor market conditions, does not achieve explanatory power close to that of county unemployment rates.

In stark contrast, in the older cohort (NLSY–79), after conditioning on racial differences in the pre-market characteristics, accounting for racial differences in transition adds no extra explanatory power, no matter if I measure transition with weeks worked in the first year post-schooling (bottom panel column (3)) or further adding state unemployment rates upon schooling completion (bottom panel column (4)).[42]

Why is the role of the school-to-work transition substantially more important in the younger cohort? Distinct from previous cohorts of Americans, the NLSY–97 cohort (early millennials) went through their early career years under the long-lasting shadow of the Great Recession. As shown in Figure 1, most of Black and white men in my NLSY–97 sample spent at least part of their first eight post-schooling years between 2008 and 2015. Although the NLSY–79 cohort also experienced smaller recessions over their early careers, it is possible that the Great Recession was particularly destructive for the job prospects of young men, and failing to transition smoothly from school to work was especially costly during the Great Recession.

In addition, it is important to emphasize that Black men completed schooling (and started their careers) at a location and time with worse labor market conditions for complicated reasons that can extend beyond simply bad luck. Past research has shown that Black workers tend to live in places with fewer job opportunities, and the relocation of firms from central cities to suburban rings has paralleled the declining Black employment rate in central cities (Hellerstein and Neumark, 2012; Miller, 2018). The observed Black disadvantage in the school-to-work transition could be, at least partially, due to barriers to geographic mobility, a lack of resources to freely choose their school-leaving time, and eventually a lack of access to job opportunities. It could also be due to discrimination against Black men in the hiring process and at the workplace, which further discourages Black men from searching and/or migrating for work.

[41] In results not presented here, when unemployment rates at entry county-year are added alone as a measure of transition, they account for about 20% of the racial labor market gaps in the NLSY–97, conditioning on the pre-market factors.

[42] In the NLSY–79, as shown in Table 6, the explanatory power of transition conditioning on pre-market factors is negative in the DFL decomposition. As explained in Section 4, this is because racial differences in the pre-market factors *more than fully* account for racial differences in transition as measured in the NLSY–79.

5.3 Understanding Observed Neighborhood Effects

My third and last finding helps us understand the documented neighborhood effects both in my data and in other studies. In an influential paper, Chetty et al. (2020) study a cohort close in age to the NLSY–97 using U.S. tax records and find that childhood neighborhood, measured by census tract (census block) fixed effects, accounts for about 30% (40%) of the observed average racial gap in income ranks. A significant limitation of their data is that they do not contain a direct measure of cognitive skills (such as the AFQT score).[43]

A vast body of evidence has shown that there is persistent residential segregation by race in the U.S., which has further limited the labor market prospects of Black Americans (e.g., Kain, 1968; Massey and Denton, 1993; Cutler and Glaeser, 1997; Charles, 2003). A critical question about Chetty et al.'s (2020) finding is to what extent the documented neighborhood effects in their data reflect the residential sorting of Black and white families and individuals into different neighborhoods, a point raised by Heckman (2018).[44] Including rich individual and family variables (especially the skill measures) in the NLSY datasets allows me to shed light on this question within the framework of the DFL decomposition.

To draw a more direct comparison to Chetty et al. (2020), in this section I focus my analysis on the NLSY–97 data, which is close in age to Chetty et al.'s (2020) sample *and* allows me to incorporate a richer set of family and (especially) neighborhood measures. Compared to the previous analysis that compares the two cohorts, here I include family and neighborhood variables available only in the NLSY–97 data. The added neighborhood variables include a measure of county neighborhood quality (Chetty and Hendren, 2018b) and homeownership status. The added family variables include mother parenting style and teenage mom status.

Table 7 presents the decomposition results for the NLSY–97 using the extended set of variables. The first three panels present the DFL decomposition results, in a similar structure as in Table 3 but with different sequential orderings, and the bottom two panels present the classical Oaxaca-Blinder linear decomposition results (which is methodologically closer to Chetty et al.

[43]Although the authors have education attainment in their data by linking tax records to the American Community Survey, the finding in Table 4 shows that it is really racial differences in measured cognitive skills, not differences in formal schooling, that have the primary explanatory power.

[44]Since its release, the findings of Chetty et al. (2020) have received tremendous attention from the press (e.g., *New York Times*, 2018; *Washington Post*, 2018) and have inspired constructive discussions among social scientists. Heckman (2018) raises a series of comments regarding both the findings of Chetty et al. (2020) and what future research needs to address. In particular, he stresses the importance of reconciling different studies in the literature, which my findings help to do.

(2020)). In the top panel where childhood neighborhood is added first in the DFL decomposition sequence and estimated unconditionally, it explains 12% of the racial employment gap and 14% of the racial earnings gap. In the fourth panel where childhood neighborhood is added *alone* in the linear Oaxaca-Blinder decomposition, it explains 24% of the racial employment gap and 18% of the racial earnings gap.

In the DFL decomposition, when family background is added before childhood neighborhood in the decomposition sequence, the contribution of neighborhood is estimated after conditioning on racial differences in family factors. This is intuitively the same as first *residualizing* the racial differences in neighborhood characteristics by the racial differences in family background.[45] If the observed racial differences in neighborhood characteristics reflect the characteristics of Black and white families living in the neighborhoods, we would expect the *residualized* racial differences in neighborhood characteristics to be much smaller than the *raw* racial differences in neighborhood characteristics. The estimated *conditional* contribution of neighborhoods will therefore be much smaller than the estimated *unconditional* contribution of neighborhoods.

Comparing the top panel with the second panel in Table 7, it is clear that after accounting for racial differences in family background, the explanatory power of childhood neighborhood decreases substantially. The share of the racial employment gap explained by childhood neighborhood goes entirely away from 12% to negative, and that of the racial earnings gap reduces from 14% to 9%.[46] When estimated further after conditioning on racial differences in education and skills (third panel in Table 7), the explanatory power of childhood neighborhood characteristics on the racial labor market gaps declines even further.[47] As a robustness check, in the bottom panel where family background and education and skills are added together with childhood neighborhood in the Oaxaca-Blinder decomposition, the explanatory power of childhood neighborhood declines to 6% for employment and 7% for earnings, from 24% and 18% (respectively) when neighborhood is included alone in the Oaxaca-Blinder decomposition (fourth panel).

This finding suggests that in the context of explaining racial labor market gaps, the ob-

[45]See Appendix B for more discussions on the methodological details.

[46]Bootstrap results show that the explanatory power of childhood neighborhood characteristics on the racial earnings gap, when estimated unconditionally, is statistically significant at the 10% level and becomes insignificant after conditioning on family background.

[47]The estimated contribution of childhood neighborhood on the racial employment gap is negative after conditioning on family background. This happens when racial differences in family characteristics *overaccount* for the observed racial differences in childhood neighborhood characteristics.

served unconditional effect of neighborhoods, at least at the level that I can observe, can result from residential sorting of families and individuals. Recall that, in sharp contrast, the estimated contribution of education and skills is generally robust whether conditional on childhood neighborhood and family background characteristics or not. While my findings do not rule out the possibility that childhood neighborhood has a true effect in explaining racial gaps in labor market outcomes, the diminishing explanatory power of measured childhood neighborhood characteristics *does* suggest that if there is a true neighborhood effect, it may well be functioning through the channel of skill formation. As previously discussed, understanding where the racial skill gap comes from requires a formal investigation of the skill formation process and the roles of family, school, and neighborhood in this process.

Although the focus of this section is to use the extended set of variables in the NLSY–97 to draw a close comparison to Chetty et al. (2020), it is important to note that I find qualitatively similar results regarding the neighborhood effects for the NLSY–79. In results not shown here, when childhood neighborhood is added first in the DFL decomposition ordering for the NLSY–79, it accounts for 63% of the racial employment gap and 13% of the racial earnings gap. As presented in the bottom panel of Table 5, when childhood neighborhood is added after conditioning on racial differences in family background, it explains 59% of the racial employment gap and 16% of the racial earnings gap, which does not seem to be meaningfully different from the unconditional explanatory power of childhood neighborhood. However, as presented in the middle panel of Table 5, when the contribution of childhood neighborhood is estimated further conditioning on racial differences in education and skills, it declines substantially and becomes negligible.[48]

It is also worth iterating that my finding here does not contradict the causal estimates of neighborhood effects in a series of recent studies (Chetty, Hendren, and Katz, 2016; Chyn, 2018; Chetty and Hendren, 2018a) but instead shows that the overall explanatory power of neighborhoods to the racial labor market gaps may be limited among young American men in today's labor market. The causal neighborhood effects in these studies are estimated by comparing disadvantaged families (many of whom are Black families) who moved to "good" neighborhoods with disadvantaged families who stayed in their original neighborhoods or by

[48]Similar to the NLSY–97 results in Table 7, the negative sign on childhood neighborhood in the middle panel of Table 5 comes from the fact that racial differences in family background and education and skills *overaccount* for the racial differences in childhood neighborhood characteristics in the NLSY–79.

comparing disadvantaged families who moved when children were younger with those who moved when children were older. This comparison, however, does not fully address the question of how the outcomes of the disadvantaged families who moved compare to families who were *already* living in the "good" neighborhoods. If, after moving, the Black families still fall substantially behind white families already living there, it indicates that the neighborhood effects, though causal and significant, actually have a limited power in explaining the overall racial income gaps, which is what my findings suggest.

6 Conclusion

How have the Black-white labor market gaps among young men changed across cohorts, and how have the underlying forces of these gaps changed? In this paper, I provide some of the first evidence on these questions with the help of two similarly constructed and nationally representative samples of young Americans, the NLSY–97 and the NLSY–79.

Tracking the early career trajectories of Black and white men in the two cohorts, I first find that the upward-sloping employment and earnings trajectories observed in the older cohort (NLSY–79) is dampened in the younger cohort (NLSY–97), especially for employment outcomes of Black men. In the older cohort, the racial employment gap in the transition stage (measured by weeks worked in first year after schooling completion) narrows substantially and significantly over the first six to eight years post-schooling. But in the younger cohort, this narrowing of initial racial employment gap is quantitatively much smaller and statistically insignificant over the early career years.

I then explore whether and how the underlying explanatory factors of the observed racial labor market gaps have changed between the two NLSY cohorts. First, I show that education and skills, especially measured cognitive skills, explain a crucial part of the racial labor market gaps in both cohorts. Importantly, I find that in the younger cohort (NLSY–97), the explanatory power of education and skills is robust even after accounting for measured racial differences in family and neighborhood characteristics. This robust and stable role of racial skill gap is not found in the older cohort (NLSY–79). Second, racial differences in the school-to-work transition (measured by weeks worked in the first year post-schooling and local labor market conditions upon schooling completion) plays a particularly important role in explaining racial labor market gaps in the younger cohort (NLSY–97). This distinctive pattern for the younger cohort is possibly driven by the fact that the younger cohort spent much of their early career years under the shadow of the Great Recession, which made an unsuccessful school-to-work transition especially consequential. Third, the estimated explanatory power of childhood neighborhood characteristics decreases substantially after conditioning on racial differences in family background and individual skills. This finding suggests that the documented neighborhood effects in previous studies (e.g. Chetty et al. 2020) either work through the channel of skill formation or reflect the residential sorting of families and individuals across neighborhoods (or both).

Given the descriptive nature of my findings, one must be cautious in drawing immediate policy implications. However, combining my findings with existing studies suggests lessons that may help guide future research and polices. Despite the dramatic changes in both the characteristics of young men and the overall structure of the U.S. labor market, cognitive skills turn out to still be the key driver of racial labor market gaps in the younger cohort, as in previous cohorts. This finding suggests that although market demand for skills might have evolved over the past few decades, cognitive skills are still rewarded in today's labor market and are particularly important in shaping racial gaps in labor market outcomes. Although the racial gap in cognitive skills (measured by AFQT scores) has narrowed across the two NLSY cohorts, the gap remains quantitatively substantial and statistically significant in the younger cohort (NLSY–97). My findings strongly suggest that more attention needs to be paid to understanding the skill accumulation process and, more importantly, Black disadvantage in this process. Potentially effective pathways to reduce racial labor market gaps include public programs that foster skill accumulation among Black men.[49]

My finding regarding the role of the school-to-work transition suggests that helping disadvantaged Black men to get a foothold in the labor market is a potentially important pathway to reduce racial labor market gaps at later career stages. In addition to traditional government training programs[50], recent examples of job training programs designed and led by non-government organizations show encouraging results for helping disadvantaged youths initiate a career (Fein and Hamadyk, 2018).[51] Policies that increase geographic mobility and the flexibility to choose school-leaving time may also help reduce Black disadvantage in the school-to-work

[49]For example, existing evidence based on previous cohorts suggests that family investments in young children have especially high returns (Cunha et al., 2006).

[50]Friedlander, Greenberg, and Robins (1997) reviews the evidence on the effectiveness of government training programs and concludes that the effects are modest on average and limited among youths.

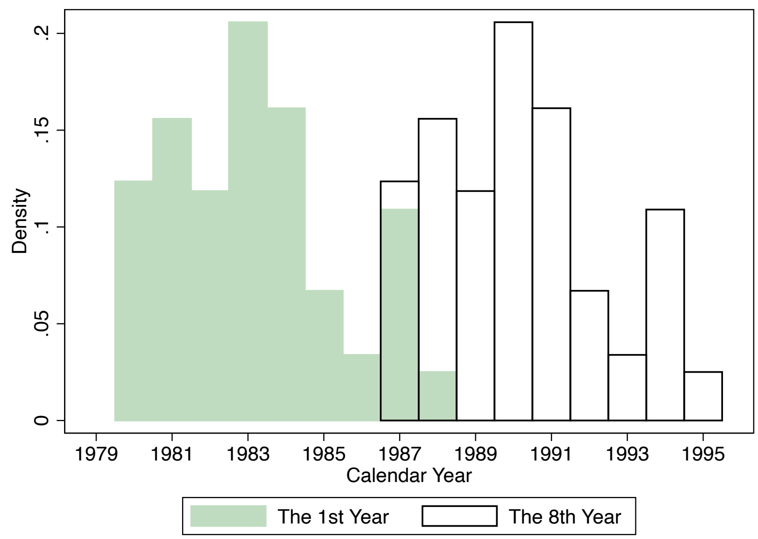
[51]I thank Peter Bergman for pointing out the innovative job training programs (e.g. Year Up) led by non-government organizations.

transition process, which will eventually help reduce racial gaps in longer-term labor market outcomes.

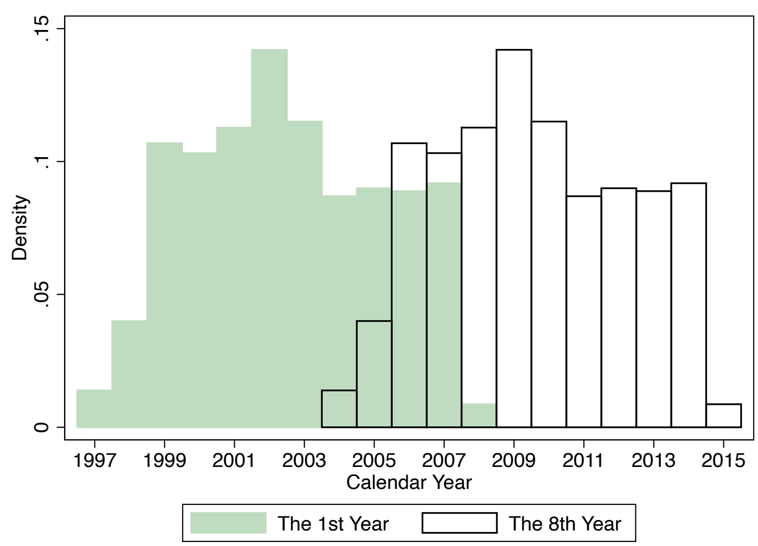
Figures and Tables

Figure 1: Corresponding Calendar Years to Sample Observations

(a) NLSY–79



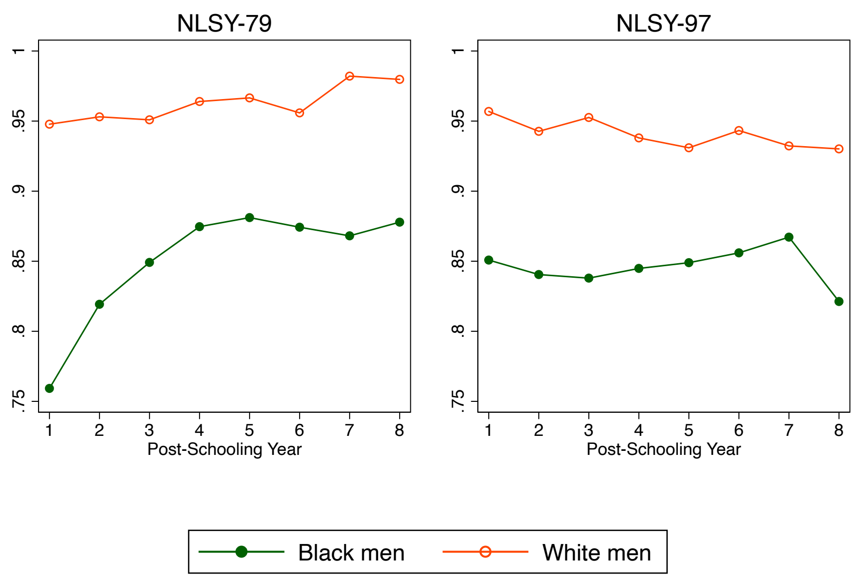
(b) NLSY–97



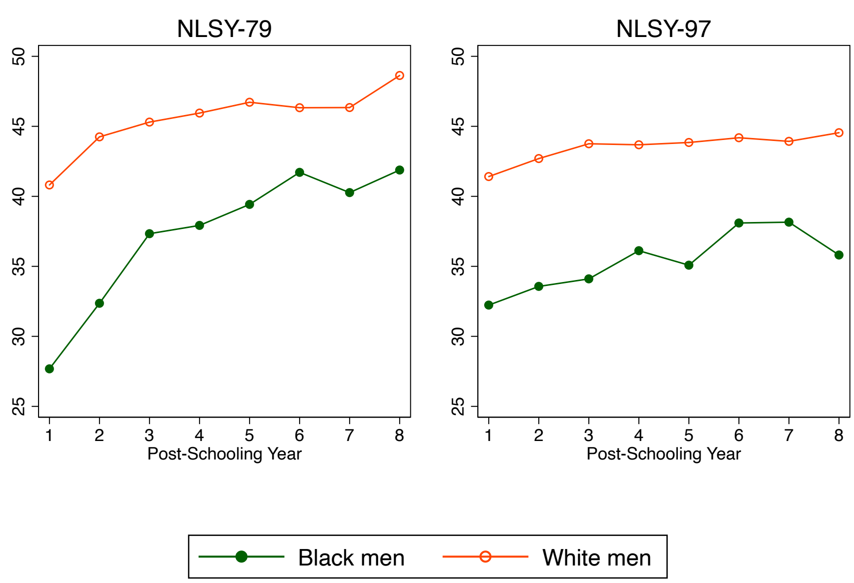
Notes: The histograms show the corresponding calendar years to the young men's first and eighth year post-schooling. Both NLSY–79 and NLSY–97 samples are balanced panels of men who have completed formal schooling for at least eight years. Sample weights are used.

Figure 2: Career Trajectories: Any Employment and Weeks Worked

(a) Any Employment



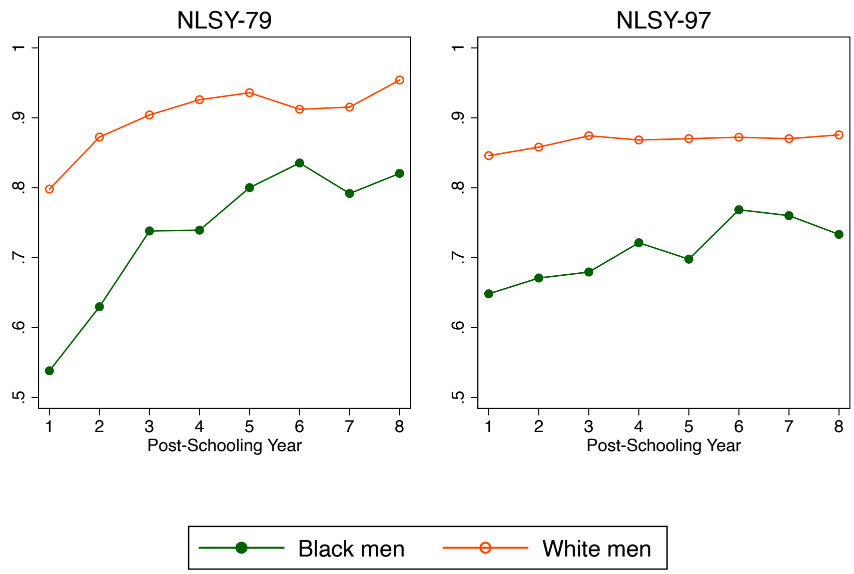
(b) Weeks Worked



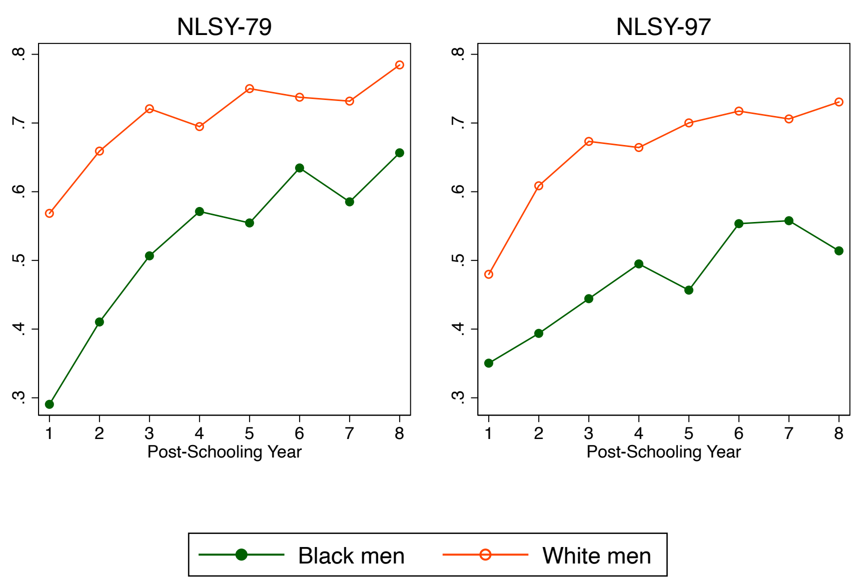
Notes: Both NLSY–79 and NLSY–97 samples are balanced panels of men who have completed formal schooling for at least eight years. Sample weights are used.

Figure 3: Career Trajectories: Worked Half Year and Full Year

(a) Worked Half Year (≥ 26 weeks)



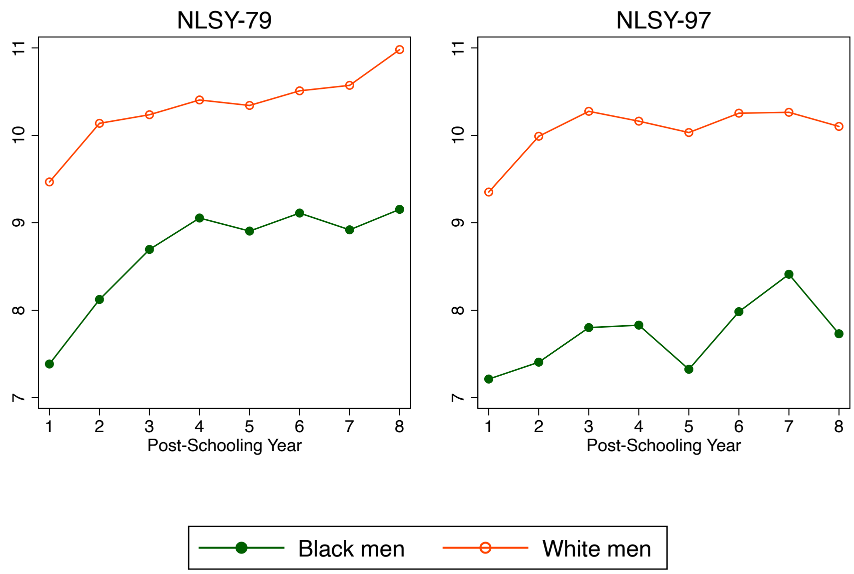
(b) Worked Full Year (≥ 50 weeks)



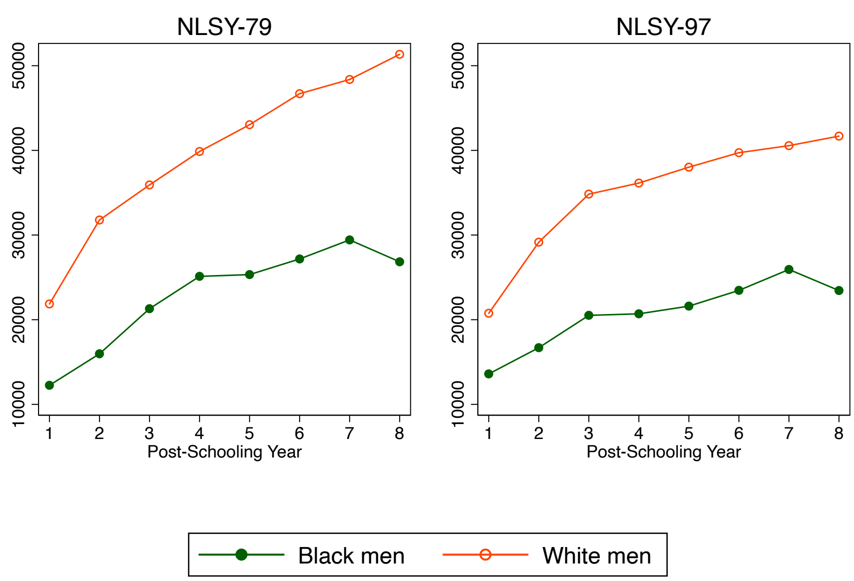
Notes: Both NLSY–79 and NLSY–97 samples are balanced panels of men who have completed formal schooling for at least eight years. Sample weights are used.

Figure 4: Career Trajectories: Annual Earnings

(a) Log Annual Earnings



(b) Annual Earnings



Notes: Annual earnings are adjusted to 2013 dollars. The top panel takes the inverse hyperbolic sine of annual earnings. Both NLSY–79 and NLSY–97 samples are balanced panels of men who have completed formal schooling for at least eight years. Sample weights are used.

Table 1: Early Career Outcomes of Black and White Men in the NLSY–79 and NLSY–97 Cohorts

	NLSY–79			NLSY–97			97–79
	White (1)	Black (2)	W-B (3)	White (4)	Black (5)	W-B (6)	(7)
Transition Stage (1st Year)							
Weeks before finding 1st job	11.89	41.97	–30.08†	10.68	32.78	–22.10†	7.98
Any employment	0.95	0.76	0.19†	0.96	0.85	0.11†	–0.08†
Worked for $\geq$ 26 weeks	0.80	0.54	0.26†	0.85	0.65	0.20†	–0.06
Worked for $\geq$ 50 weeks	0.57	0.29	0.28†	0.48	0.35	0.13†	–0.15†
Weeks worked	40.81	27.68	13.13†	41.41	32.23	9.18†	–3.95
Log annual earnings	9.47	7.38	2.08†	9.35	7.21	2.14†	0.06
Later Stage (6th–8th Year)							
Weeks worked per year	47.10	41.33	5.78†	44.20	37.30	6.90†	1.12
Log average annual earnings	10.93	9.56	1.37†	10.55	9.01	1.54†	0.17
Growth from 1st to 6th–8th Year							
Weeks worked per year	6.29	13.65	-7.36†	2.80	5.07	-2.27	5.09†
Log average annual earnings	1.48	2.14	-0.66	1.20	1.79	-0.58	0.58
Summarizing First 8 Years							
Number of NE spells	1.68	2.30	–0.62†	1.77	2.66	–0.89†	–0.28
Avg. months of NE spells	6.99	9.51	–2.52	6.47	10.14	–3.66†	–1.14
Cumulative weeks worked	363.92	297.75	66.17†	347.15	282.56	64.59†	–1.58
Weeks worked per year	45.54	37.29	8.25†	43.50	35.40	8.10†	–0.15
Log average annual earnings	11.04	10.01	1.03†	10.73	9.48	1.25†	0.22

[1] The NLSY–79 sample includes 444 white men and 271 Black men, and the NLSY–97 sample includes 825 white men and 396 Black men. Both samples are balanced panels of men who have completed formal schooling for at least eight years. Section 2 explains how the samples are constructed. Sample weights are used.
[2] † indicates a p-value below 0.05.
[3] NE stands for non-employment.

Table 2: Descriptive Characteristics of Black and White Men in the NLSY–79 and NLSY–97 Cohorts

	NLSY–79			NLSY–97			97–79
	White (1)	Black (2)	W-B (3)	White (4)	Black (5)	W-B (6)	(7)
Education and Skills							
HGC	13.46	12.80	0.66†	13.13	12.08	1.05†	0.39
AFQT percentile	58.61	22.93	35.68†	51.06	25.76	25.31†	–10.37†
Social score	0.03	0.20	–0.18	–0.05	–0.22	0.17†	0.35†
Non-cognitive score	0.07	–0.06	0.13	–0.12	–0.07	–0.05	–0.18
Family Background							
Log parental income	11.56	10.85	0.72†	10.96	8.94	2.01†	1.30†
Mother's HGC	12.07	11.13	0.94†	13.03	12.45	0.59†	–0.35
Living with both parents	0.85	0.56	0.28†	0.62	0.32	0.31†	0.02
Childhood Neighborhood							
Residence Type							
MSA, central city	0.06	0.36	–0.30†	0.21	0.36	–0.15†	0.14†
MSA, non-central city, urban	0.58	0.39	0.20†	0.33	0.22	0.12†	–0.08
MSA, non-central city, rural	0.04	0.00	0.04†	0.20	0.19	0.01	–0.03
Non-MSA, rural	0.19	0.17	0.02	0.18	0.15	0.03	0.01
County Conditions							
Log population	12.26	12.60	–0.35†	12.14	12.35	–0.21	0.13
Log median HH income	10.93	10.78	0.15†	10.95	10.87	0.08†	–0.07†
Poverty rate	0.11	0.17	–0.06†	0.11	0.16	–0.04†	0.02†
Male college rate	0.19	0.18	0.01	0.24	0.23	0.01	0.00
State Conditions							
Log population	15.75	15.65	0.10	15.79	15.76	0.03	–0.07
Log median HH income	10.91	10.85	0.07†	10.98	10.94	0.04†	–0.03
Poverty rate	0.12	0.14	–0.03†	0.12	0.13	–0.01†	0.02†
Male college rate	0.20	0.19	0.01†	0.26	0.25	0.01†	0.00

[1] HGC stands for highest grade completed. AFQT stands for the Armed Forces Qualification Test. MSA stands for metropolitan statistical area. HH stands for household. The NLSY–79 sample includes 444 white men and 271 Black men, and the NLSY–97 sample includes 825 white men and 396 Black men. Both samples are balanced panels of men who have completed formal schooling for at least eight years. Section 2 explains how the samples are constructed. Sample weights are used.

[2] † indicates a p-value below 0.05.

Table 3: DFL Sequential Decomposition (NLSY–97)

	W-B Gap	Share Explained by			Residuals
NLSY–97					
Sequential Ordering I		Skill	Family	NBHD	
Weeks worked per year	6.90	27%	32%	-7%	48%
Log avg annual earnings	1.54	30%	18%	13%	39%
Sequential Ordering II		Family	Skill	NBHD	
Weeks worked per year	6.90	34%	25%	-7%	48%
Log avg annual earnings	1.54	20%	29%	13%	39%
Sequential Ordering III		Family	NBHD	Skill	
Weeks worked per year	6.90	34%	-6%	24%	48%
Log avg annual earnings	1.54	20%	9%	33%	39%

[1] DFL stands for the DiNardo-Fortin-Lemieux decomposition, and NBHD stands for neighborhood. The sample is a balanced panel of 825 white men and 396 Black men who have completed formal schooling for at least eight years. Sample weights are used.

[2] The number of weeks worked per year is averaged over the sixth to eighth years. The annual earnings are averaged over the sixth to eighth years and then take the inverse hyperbolic sine.

Table 4: Is it Schooling or Measured Cognitive Skills? (NLSY–97)

	W-B Gap	Share Explained by			Residuals
Skill includes only HGC		Skill	Family	NBHD	
Avg weeks worked per year	6.90	14%	22%	-7%	70%
Log avg annual earnings	1.54	12%	10%	9%	69%
		Family	Skill	NBHD	
Avg weeks worked per year	6.90	34%	3%	-7%	70%
Log avg annual earnings	1.54	20%	3%	9%	69%
		Family	NBHD	Skill	
Avg weeks worked per year	6.90	34%	-6%	1%	70%
Log avg annual earnings	1.54	20%	9%	3%	69%
Skill includes only AFQT		Skill	Family	NBHD	
Avg weeks worked per year	6.90	28%	31%	-8%	49%
Log avg annual earnings	1.54	30%	16%	13%	41%
		Family	Skill	NBHD	
Avg weeks worked per year	6.90	34%	25%	-8%	49%
Log avg annual earnings	1.54	20%	26%	13%	41%
		Family	NBHD	Skill	
Avg weeks worked per year	6.90	34%	-6%	23%	49%
Log avg annual earnings	1.54	20%	9%	30%	41%

[1] The top panel includes only highest grade completed (HGC) in the skill set, the bottom panel includes only Armed Forces Qualification Test (AFQT) score in the skill set. I use the AFQT score adjusted by Altonji, Bharadwaj, and Lange (2012).

[2] NBHD stands for neighborhood. The sample is a balanced panel of 825 white men and 396 Black men who have completed formal schooling for at least eight years. Sample weights are used.

[3] The number of weeks worked per year is averaged over the sixth to eighth years. The annual earnings are averaged over the sixth to eighth years and then take the inverse hyperbolic sine.

Table 5: DFL Sequential Decomposition (NLSY–79)

NLSY–79	W-B Gap	Share Explained by			Residuals
Sequential Ordering I		Skill	Family	NBHD	
Weeks worked per year	5.78	64%	18%	-8%	27%
Log avg annual earnings	1.37	67%	18%	-26%	41%
Sequential Ordering II		Family	Skill	NBHD	
Weeks worked per year	5.78	51%	30%	-8%	27%
Log avg annual earnings	1.37	67%	17%	-26%	41%
Sequential Ordering III		Family	NBHD	Skill	
Weeks worked per year	5.78	51%	59%	-37%	27%
Log avg annual earnings	1.37	67%	16%	-25%	41%

[1] DFL stands for the DiNardo-Fortin-Lemieux decomposition, and NBHD stands for neighborhood. The sample is a balanced panel of 444 white men and 271 Black men who have completed formal schooling for at least eight years. Sample weights are used.

[2] The number of weeks worked per year is averaged over the sixth to eighth years. The annual earnings are averaged over the sixth to eighth years and then take the inverse hyperbolic sine.

Table 6: Role of the School-to-Work Transition

		Share Explained by			
	W-B Gap (1)	Pre-Market Factors (2)	Weeks worked in 1st Year (3)	Col (3) +State UR (4)	Col (3) +County UR (5)
NLSY–97					
Weeks worked per year	6.90	52%	13%	3%	18%
Log avg annual earnings	1.54	61%	13%	3%	21%
NLSY–79					
Weeks worked per year	5.78	73%	–5%	–14%	
Log avg annual earnings	1.37	59%	–14%	–4%	

[1] UR stands for unemployment rates. County-level UR data, from the Local Area Unemployment Statistics (LAUS) program, go back to 1990 and is unavailable for most of my NLSY–79 sample years. The top panel uses the NLSY–97 sample and the bottom panel uses the NLSY–79 sample. Sample weights are used.

[2] Column 2 presents the overall explanatory power of pre-market characteristics (Skill, Family, Neighborhood). Columns 3-5 present the explanatory power of various school-to-work transition measures, estimated conditioning on the pre-market characteristics. Column 3 measures transition with a flexible vector of weeks worked in the first year post-schooling. Column 4, in additional to the transition measure in Column 3, adds UR in one's state of residence at the labor market entry year. Column 5, in addition to Column 3, adds UR in one's county of residence at the labor market entry year. The numbers shown in Columns 4-5 are the *additional* explanatory power of the specific transition measure, upon the explanatory power of weeks worked in the first year.

[3] The number of weeks worked per year is averaged over the sixth to eighth years. The annual earnings are averaged over the sixth to eighth years and then take inverse hyperbolic sine.

Table 7: Understanding the Neighborhood Effects (NLSY–97)

NLSY–97	W-B Gap	Share Explained by			Residuals
Sequential Ordering I		NBHD	Family	Skill	
Weeks worked per year	6.90	12%	16%	32%	40%
Log avg annual earnings	1.54	14%	19%	38%	29%
Sequential Ordering II		Family	NBHD	Skill	
Weeks worked per year	6.90	35%	-7%	32%	40%
Log avg annual earnings	1.54	25%	9%	38%	29%
Sequential Ordering III		Family	Skill	NBHD	
Weeks worked per year	6.90	35%	38%	-12%	40%
Log avg annual earnings	1.54	25%	40%	6%	29%
Oaxaca-Blinder		NBHD			
Weeks worked per year	6.90	24%			
Log avg annual earnings	1.54	18%			
Oaxaca-Blinder		NBHD	Family	Skill	
Weeks worked per year	6.90	6%	26%	25%	
Log avg annual earnings	1.54	7%	22%	23%	

[1] NBHD stands for neighborhood. The top three panels present the DiNardo-Fortin-Lemieux decomposition results, and the bottom two panels present the Oaxaca-Blinder decomposition results.

[2] Compared to Table 3, this table further incorporates family and neighborhood variables that are available only in the NLSY–97 data. Neighborhood variables further include a measure of county neighborhood quality (Chetty and Hendren, 2018b) and home ownership status. Family variables further include mother parenting style and teenage mom status. Sample weights are used.

[3] The number of weeks worked per year is averaged over the sixth to eighth years. The annual earnings are averaged over the sixth to eighth years and then take the inverse hyperbolic sine.

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A Appendix Tables and Figures

Table A.1: DFL Sequential Decomposition (NLSY–97, Bootstrap Results)

	W-B Gap	Explained Gap			Residuals
NLSY–97					
Sequential Ordering I		Skill	Family	NBHD	
Weeks worked per year	6.90	$1.86^{\dagger}$	$2.21^{\dagger}$	-0.48	3.31
Log avg annual earnings	1.54	$0.46^{\dagger}$	$0.28^{\dagger}$	$0.20^{\S}$	0.60
Sequential Ordering II		Family	Skill	NBHD	
Weeks worked per year	6.90	$2.35^{\dagger}$	$1.73^{\dagger}$	-0.48	3.31
Log avg annual earnings	1.54	$0.31^{\dagger}$	$0.45^{\dagger}$	$0.20^{\S}$	0.60
Sequential Ordering III		Family	NBHD	Skill	
Weeks worked per year	6.90	$2.35^{\dagger}$	-0.41	$1.67^{\dagger}$	3.31
Log avg annual earnings	1.54	$0.31^{\dagger}$	0.14	$0.51^{\dagger}$	0.60

[1] This table present bootstrap results for 5,000 times. † (§) indicates a *p*-value below 0.05 (0.10). Note that the table shows the explained *gap* instead of the explained *share*.

[2] DFL stands for the DiNardo-Fortin-Lemieux decomposition, and NBHD stands for neighborhood. The sample is a balanced panel of 825 white men and 396 Black men who have completed formal schooling for at least eight years. Sample weights are used.

[3] The number of weeks worked per year is averaged over the sixth to eighth years. The annual earnings are averaged over the sixth to eighth years and then take the inverse hyperbolic sine.

Table A.2: DFL Sequential Decomposition (NLSY–79, Bootstrap Results)

NLSY–79	W-B Gap	Explained Gap			Residuals
Sequential Ordering I		Skill	Family	NBHD	
Weeks worked per year	5.78	3.70†	1.04	-0.46	1.56
Log avg annual earnings	1.37	0.92†	0.25	-0.36	0.56
Sequential Ordering II		Family	Skill	NBHD	
Weeks worked per year	5.78	2.95†	1.73	-0.46	1.56
Log avg annual earnings	1.37	0.92†	0.23	-0.36	0.56
Sequential Ordering III		Family	NBHD	Skill	
Weeks worked per year	5.78	2.95†	3.41†	-2.14	1.56
Log avg annual earnings	1.37	0.92†	0.22	-0.34	0.56

[1] This table present bootstrap results for 5,000 times. † (§) indicates a *p*-value below 0.05 (0.10). Note that the table shows the explained *gap* instead of the explained *share*.

[2] DFL stands for the DiNardo-Fortin-Lemieux decomposition, and NBHD stands for neighborhood. The sample is a balanced panel of 444 white men and 271 Black men who have completed formal schooling for at least eight years. Sample weights are used.

[3] The number of weeks worked per year is averaged over the sixth to eighth years. The annual earnings are averaged over the sixth to eighth years and then take the inverse hyperbolic sine.

B Decomposition Method

In this Appendix, I describe the decomposition method (DiNardo, Fortin, and Lemieux (1996, hereafter DFL)) that I use for the main analysis of the paper. I first describe how the DFL method works under the context of explaining racial labor market gaps, and then discuss how to interpret the DFL estimates and relate them to other estimates in the literature.

B.1 Aggregate Decomposition

Let $f_w(y)$ be the density of labor market outcome y (such as employment or earnings) for white men and $f_b(y)$ for Black men. Let Z represent a vector of observed individual-, family-, and neighborhood-level characteristics that have an impact on one's labor market outcome y. The counterfactual density of y for white men who had the observed characteristics of Black men can be written as $f_w(y; Z_b)$. Intuitively, this counterfactual holds the *relationship* between y and Z as fixed for white men. The DFL method keeps this relationship non-parametric, so no specific functional form is imposed on $f_w()$.

Using this counterfactual, I can conduct the following decomposition of the racial gap in outcome y:

$$\begin{aligned} f_w(y) - f_b(y) &= f_w(\, y; Z_w\,) - f_w(\, y; Z_b\,) \\ &+ f_w(\, y; Z_b\,) - f_b(\, y; Z_b\,). \end{aligned} \tag{1}$$

The first line in Equation 1 represents the racial gap that can be explained by Black-white differences in observed characteristics Z (also known as "quantities"). The second line, which represents the unexplained residuals, include the contributions of 1) Black-white differences in *unobserved* characteristics and 2) Black-white differences in the *returns* (also known as "prices") paid to observed and unobserved characteristics. For example, if Black men receive lower labor market returns (such as less working time and/or lower wages) to the same characteristics due to discrimination, the racial differences in returns will be left in the unexplained residuals.[52]

[52] Equivalently, in principle one can conduct an alternative decomposition using $f_b(y; Z_w)$, the counterfactual outcome for Black men if they had the observed characteristics of white men. Conducting this reverse decomposition will introduce a common support problem, which has been discussed in earlier studies (Barsky et al., 2002; Heywood and Parent, 2012). Another distinction between the decomposition in Equation 1 and this reverse decomposition is whether $f_w()$, the earnings or employment function for white men, or $f_b()$, the function for Black men, is used. Under the context of racial labor market gaps, the literature usually uses $f_w()$ for decomposition analysis, mainly because the earnings or employment function received by white men is arguably more similar to

B.2 Sequential Detailed Decomposition

In addition to the *aggregate* decomposition, the DFL method allows me to estimate the contribution of different subsets of variables in Z to the racial gap in labor market outcome y. This *detailed* decomposition helps answer questions such as "What labor market outcomes would white men have achieved if they had the same family background and education and skills as Black men in the same cohort but kept their original childhood neighborhood characteristics and the school-to-work transition?"

Let Z consist of four main subsets of variables: family background F, childhood neighborhood N, education and skills S, and the school-to-work transition T. One of the possible detailed decompositions can be written as

$$\begin{aligned} f_w(y) - f_b(y) &= f_w(\,y\,) - f_w(\,y; F_b, N_w, S_w, T_w\,) \\ &+ f_w(\,y; F_b, N_w, S_w, T_w\,) - f_w(\,y; F_b, N_b, S_w, T_w\,) \\ &+ f_w(\,y; F_b, N_b, S_w, T_w\,) - f_w(\,y; F_b, N_b, S_b, T_w\,) \\ &+ f_w(\,y; F_b, N_b, S_b, T_w\,) - f_w(\,y; F_b, N_b, S_b, T_b\,) \\ &+ f_w(\,y; F_b, N_b, S_b, T_b\,) - f_b(\,y\,). \end{aligned} \tag{2}$$

The first line represents the contribution of Black-white differences in family background F. The contribution is the sum of a *direct* effect of family background F on labor market outcome y and an *indirect* effect, which comes from any changes in the distributions of N, S, and T that are attributed to the changes in F. In other words, this is the *unconditional* effect of family background on the racial gap in y.

The second line represents the contribution of Black-white differences in childhood neighborhood N *after* accounting for Black-white differences in family background characteristics. It is important to note that when holding family background constant between Black and white men, any variations in neighborhood characteristics that are implied by variations in family characteristics are also held to be constant between Black and white men. The third and fourth lines can be interpreted in a similar fashion as a conditional contribution of education and skills and the school-to-work transition, respectively. The last line represents the racial gap in y that

the hypothetical earnings or employment function in a labor market without discrimination (or other institutional barriers) against Black men. I therefore stick to the decomposition in Equation 1 throughout my analysis.

remains unexplained after accounting for Black-white differences in all observed factors in Z.[53]

An important feature of the DFL decomposition is that the detailed decomposition is not unique. As is shown in Equation 2, the contributions of different components of Z to the overall racial gap depend on the sequential ordering by which the different components (F, N, S, and T) are added into the decomposition. The components that are added earlier in the sequence are given more credit in explaining the racial gap. The merit of any sequential ordering depends on how the different components are causally related to the others. Under a similar context, Altonji, Bharadwaj, and Lange (2012) argue that a natural ordering is the one that follows the *timing* of variables.

In my empirical analysis, I explore different choices of sequential orderings as in a permutation exercise. Across all orderings, I always keep the school-to-work transition as the last component after all "pre-market" factors (F, N, and S), because one's transition performance is presumably an outcome of "pre-market" factors. Otherwise, I hold no prior as to where F, N, and S should be in the sequence relative to each other.

B.3 Interpreting DFL Decomposition Estimates

To help illustrate the DFL estimates and draw a more direct comparison to other estimates in the literature, in this section I first impose some additional structure on the DFL method following Altonji, Bharadwaj, and Lange (2012). Note that this section is for illustrative purpose only, and my main decomposition analysis does not require the additional structure discussed here.

Under linearity and additional separability assumptions, we can write down the relationship between outcome y and the underlying characteristics as

$$E(\,y; F, N, S, T\,) \quad = \quad \beta_0 + \beta_f F + \beta_n N + \beta_s S + \beta_t T, \tag{3}$$

where β is the partial effect of each underlying factor on y. This is the classical linear regression that many studies in the literature rely on.

To see how the DFL decomposition works, further assume that the relationship between the

[53] It is important to iterate that the DFL decomposition focuses on how much of the racial gaps in y can be explained by racial differences in N, F, S, and T ("quantities"), and it does not reveal the potential effect of racial differences in the returns paid to each one of these factors ("prices"), which will be absorbed in the residuals.

underlying factors is also linear and separable.[54] In a specific sequential decomposition, this assumption allows us to write the lower-order component as a linear and additive function of the higher-order components. For example, in the decomposition of Equation 2, we can write childhood neighborhood characteristics as a function of family background:

$$E(\,N; F\,) \quad = \quad \gamma_{0,n} + \gamma_{f,n}F, \tag{4}$$

where $\gamma_{f,n}$ is the partial effect of F on N. This equation only includes F on the right-hand side because F is the only factor added before N in the decomposition sequence.

Under these assumptions, the DFL sequential decomposition estimates can be written out *explicitly*. Take the decomposition of Equation 2 as an example. The contribution of family background F, which is added first in the sequence, can be expressed as

$$(\,F_w - F_b\,) \times (\,\beta_f + \gamma_{f,n}\beta_n + \gamma_{f,s}\beta_s + \gamma_{f,t}\beta_t\,). \tag{5}$$

The estimated contribution of F is the sum of two terms: 1) the partial effect of F on y, as represented by $(\,F_w - F_b\,) \times \beta_f$, and 2) an *indirect* effect on y that arises because shifts in F lead to shifts in N, S, and/or T, represented by $(\,F_w - F_b\,) \times (\,\gamma_{f,n}\beta_n + \gamma_{f,s}\beta_s + \gamma_{f,t}\beta_t\,)$.[55]

The contribution of childhood neighborhood N, which is added after F in the sequence shown in Equation 2, can be expressed as

$$(\,\widetilde{N}_w - \widetilde{N}_b\,) \times (\,\beta_n + \gamma_{n,s}\beta_s + \gamma_{n,t}\beta_t\,), \tag{6}$$

where $\widetilde{N}_w - \widetilde{N}_b = (\,N_w - N_b\,) - \gamma_{f,n}(\,F_w - F_b\,)$ is the *residualized* racial differences in N by F.

If racial differences in childhood neighborhood characteristics can be fully (or more than fully) accounted for by racial differences at the family level, the estimated contribution of N could be close to zero (or negative). In practice, it is not uncommon for DFL decomposition to produce estimates with a negative sign (e.g., DiNardo, Fortin, and Lemieux, 1996; Altonji, Bharadwaj, and Lange, 2012).

Similarly, the contribution of education and skills S, which is added after F and N in the

[54] See Altonji, Bharadwaj, and Lange (2012) for a detailed introduction of the assumptions.

[55] Altonji, Bharadwaj, and Lange (2012) call Equation 5 the "sequential marginal effect."

sequence, can be written as

$$(\widetilde{S}_w - \widetilde{S}_b) \times (\beta_s + \gamma_{s,t}\beta_t), \tag{7}$$

where $\widetilde{S}_w - \widetilde{S}_b = (S_w - S_b) - \gamma_{f,s}(F_w - F_b) - \gamma_{n,s}(N_w - N_b)$ is the *residualized* racial differences in S by F and N.

B.3.1 Relation to Other Estimates in the Literature

How does the DFL sequential decomposition estimate relate to other estimates in the literature? Here I discuss two types of estimates in particular, using the neighborhood effect literature as an example. The two estimates are 1) the estimated causal effect of neighborhoods and 2) the estimated contribution of neighborhoods to racial labor market gaps based on linear regressions.

First, a series of papers have estimated the causal effect of growing up in "good" neighborhoods (Chetty, Hendren, and Katz, 2016; Chyn, 2018; Chetty and Hendren, 2018a).[56] In Equation 6, the causal effect of neighborhood is represented by β_n. Conceptually, the contribution of neighborhoods estimated in the DFL decomposition therefore nests the causal estimates of neighborhood established in the literature, although β_n is not directly estimated in the DFL decomposition. An important implication from Equation 6 is that even when there is a causal neighborhood effect ($\beta_n > 0$), the explanatory power of neighborhood to the observed racial labor market gaps can still be limited if the *residualized* Black-white differences in childhood neighborhood characteristics are quantitatively small.

Second, an alternative approach to estimate the contribution of neighborhoods uses linear regressions (or decomposition methods based on linear regressions, e.g., Oaxaca-Blinder decomposition). One example is of this approach is Chetty et al. (2020). Like the DFL decomposition, the estimates in this series of literature are also mainly descriptive. Using terminology in this section, the linear-regression-based estimates can be written as $(N_w - N_b) \times \beta_n$.

The DFL estimate in Equation 6 differs from the linear-regression-based estimate in two ways. The first and major distinction is that the DFL estimate uses the *residualized* racial differences in neighborhood characteristics ($\widetilde{N}_w - \widetilde{N}_b$) rather than the raw differences ($N_w - N_b$). As pointed out by Heckman (2018), to identify the true contribution of neighborhoods, it is

[56]The causal effect in this recent literature is usually estimated by comparing families (and children in these families) who move to "good" neighborhoods with families who stay in disadvantaged neighborhoods.

important to rule out the part of the raw racial differences in neighborhood characteristics ($N_w - N_b$) that reflect the residential sorting of Black and white families and individuals across neighborhoods. This is exactly what the residualized racial differences ($\widetilde{N}_w - \widetilde{N}_b$) help identify. The second distinction is that the DFL estimate includes the indirect effect that works through lower-order components in the sequence.[57]

B.4 Estimating the Counterfactual

The DFL method constructs the counterfactual $f_w(y; Z_b)$ by *reweighting* the joint distribution of (y, Z) for white men so that the *reweighted* distribution of Z for white men matches the distribution of Z for Black men. To see how the weight is determined, the counterfactual density $f_w(y; Z_b)$ is written as the following integral of the conditional density $f_w(\, y \mid z\,)$ over the Z distribution of Black men:

$$\begin{aligned} f_w(\, y; Z_b\,) &= \int f_w(\, y \mid z\,)\; dF_b(z) \\ &= \int f_w(\, y \mid z\,)\; \psi(z)\; dF_w(z), \end{aligned}$$

where the weight $\psi(z) = dF_b(z)/dF_w(z)$. Applying Bayes's rule, I rewrite the weight as

$$\psi(z) \;\; = \;\; \frac{dF_b(z)}{dF_w(z)} = \frac{Pr(z \mid b)}{Pr(z \mid w)} = \frac{Pr(b \mid z)}{Pr(w \mid z)} \frac{Pr(w)}{Pr(b)},$$

where $Pr(b \mid z)$ is the probability of being Black given on observed characteristics z and $Pr(b)$ is the unconditional probability of being Black. $Pr(b \mid z)$ can be estimated with a probit model that includes the full vector of z, and $Pr(b)$ can be estimated with the sample fraction of Black men. $Pr(w \mid z)$ and $Pr(w)$ can be estimated similarly. When estimating $Pr(b \mid z)$ and $Pr(w \mid z)$ with probit models, I impose parametric functional forms. Doing this makes the DFL method semi-parametric, not completely non-parametric.

Similar to propensity score matching, a practical issue in the DFL decomposition is how to deal with extremely large weights. Intuitively, the weight $\psi(z)$ will be large if the characteristics vector z is very rare among white men. In this case, $Pr(z \mid w)$ will be very small and $Pr(z \mid b)$

[57]Note that the DFL decomposition does not impose any functional form assumptions on the relationship between the outcome and the underlying factors, although in this section I impose linear and additive structures for illustrative purposes. This is another distinction between the DFL estimate and linear-regression-based estimates.

will be very large, which drives up the weight $\psi(z)$. In practice, I first adjust the weight $\psi(z)$ to have a mean of one and then cap the weight at the value of 20, under the prior that any weights above 20 should be due to sampling errors. What this capping does is basically *down-weight* white men who share similar observed characteristics z with Black men in the sample. By down-weighting these white men, the explanatory power of z to the racial gaps in y is also adjusted down.[58]

The counterfactuals in the detailed decomposition, as in Equation 2, can be estimated in a similar way. For example, write $f_w(\, y; F_b, N_b, S_w, T_w \,)$, the counterfactual density of y for white men when they had the same family background and childhood neighborhood as Black men, as the following integral:

$$\begin{aligned} f_w(\, y; F_b, N_b, S_w, T_w \,) &= \int f_w(\, y \mid f, n\,;\, S_w, T_w \,)\; dF_b(f, n) \\ &= \int f_w(\, y \mid f, n\,;\, S_w, T_w \,)\; \phi(f, n)\; dF_w(f, n). \end{aligned}$$

Using Bayes's rule, I can rewrite the weight $\phi(f, n)$ as

$$\psi(f, n) \;=\; \frac{dF_b(f, n)}{dF_w(f, n)} = \frac{Pr(b \mid f, n)}{Pr(w \mid f, n)} \frac{Pr(w)}{Pr(b)}.$$

As explained earlier, $Pr(b \mid f, n)$ and $Pr(w \mid f, n)$ can be estimated with a probit model that includes F and N as explanatory variables, and $Pr(w)$ and $Pr(b)$ can be estimated with the sample share of white and Black men. The same procedure can be applied to estimate other counterfactuals as well as the associated weights.

[58] Note that Altonji, Bharadwaj, and Lange (2012) also cap the weights in a similar context, where they reweight the NLSY–79 sample to make it similar to the NLSY–97 sample. My results are qualitatively robust to different choices of weight caps.