

Black–white differences in intergenerational economic mobility in the United States

Bhashkar Mazumder

Introduction and summary

The large and persistent gap in economic status between blacks and whites in the United States has been a topic of considerable interest among social scientists and policymakers for many decades. The historical legacy of slavery and segregation raises the question of how long black Americans are likely to remain a disadvantaged minority. Despite the enormous literature on black–white inequality and its historical trends, few studies have directly measured black–white differences in rates of intergenerational mobility, that is, the ability of families to improve their position in the income distribution from one generation to the next. Estimates of rates of intergenerational mobility by race can provide insight on whether racial differences in the United States are likely to be eliminated and, if so, how long it might take. Furthermore, they might also help inform policymakers as to whether there are lingering racial differences in equality of opportunity and, if so, what the underlying sources for these differences are.

More generally, the relatively low rate of intergenerational mobility in the United States compared with other industrialized countries has been a growing concern to policymakers across the political spectrum.¹ Understanding the sources of racial differences in intergenerational mobility might also shed light on the mechanisms behind the relatively high degree of intergenerational persistence of inequality in the United States.

In this study, I attempt to advance our understanding along several dimensions. First, I use two data sets containing larger intergenerational samples than have been used in the previous literature. One of the data sets matches individuals in the U.S. Census Bureau’s *Survey of Income and Program Participation* (SIPP) to administrative earnings records from the Social Security Administration (SSA). This matched data set provides many more years of data on parents’

earnings than most surveys and is likely to be less prone to measurement error, since it is derived from tax records. In addition, the SIPP contains data on

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key characteristics of the parents, such as wealth levels and marital history. The other data source I use is the U.S. Bureau of Labor Statistics' *National Longitudinal Survey of Youth* (NLSY). In addition to containing a rich array of information as children transition from adolescence to adulthood, such as test scores and personality traits, the NLSY also measures total family income in both generations, giving it an advantage over the SIPP. Using a measure of economic status that includes the income of the spouse avoids selecting only women who participate in the labor market.

Second, I use two types of measures of intergenerational mobility. The first is a set of transition probabilities of relative income status across generations. An example is the probability of moving out of the bottom quintile of the income distribution from one generation to the next. Hertz (2005) was the first to use transition probabilities to examine black–white differences in intergenerational mobility. Using the Panel Study of Income Dynamics (PSID), Hertz found that blacks were less upwardly mobile and more downwardly mobile over generations than whites. Since then, a few other studies mostly using the PSID have found similar results.²

The second set of measures, called directional rank mobility, compares whether the rank of a child in the income distribution is higher or lower than their parents' rank in the previous generation.³ Both types of measures are able to distinguish upward movements from downward ones and can be measured at different points in the income distribution. The directional rank mobility measure is a useful complement to the transition probability because instead of using an arbitrarily chosen cutoff, it uses a natural yardstick, one's own parents' rank. As I discuss later, the directional rank mobility measures also appear to be very robust to many measurement issues.

A key finding is that in recent decades, blacks have experienced substantially less upward intergenerational mobility and substantially more downward intergenerational mobility than whites. These results are shown to be highly robust to a variety of measurement issues, such as the concept of income used, the age of the sample members, and the length of the time average used. The results are found in two different data sets that cover different birth cohorts and differ in their gender composition. Moreover, these results utilize relatively large samples of black families, so that racial differences can be shown to be statistically significant. An important implication of the results that has not been shown explicitly before is that if these patterns of mobility were to persist into the future, the implications for racial differences in the “steady-state” distribution

of income would be alarming. Instead of eventually “regressing to the mean,” as some traditional measures of intergenerational mobility (when applied to the whole population) would suggest, these results imply that black Americans would make no further relative progress. Of course, it is a strong hypothetical to assume that current rates of mobility will hold in future generations. Indeed, over the past 150 years, there have been clear periods in which the racial gap in economic status has narrowed and it is certainly possible that black–white gaps could converge.⁴

This study also tries to shed light on which factors are associated with the racial gaps in upward and downward mobility. To be clear, while the analysis is descriptive and not causal, it nonetheless provides some highly suggestive “first-order” clues for the underlying mechanisms leading to black–white differences in intergenerational mobility. It appears that cognitive skills during adolescence, as measured by scores on the Armed Forces Qualification Test (AFQT), are strongly associated with these gaps. For example, conditional on having the median AFQT score, the racial gaps in both upward and downward mobility are relatively small.⁵ Consistent with previous studies linking AFQT scores to racial differences in adult outcomes (for example, Neal and Johnson, 1996; Cameron and Heckman, 2001), I do not interpret these scores as measuring innate endowments but rather as reflecting the accumulated differences in family background and other influences that are manifested in test scores.⁶ If these results are given a causal interpretation, they suggest that actions that reduce the racial gap in test scores could also reduce the racial gap in intergenerational mobility.⁷

A commonly proposed explanation for racial gaps in achievement has been the relatively high rates of black children growing up with single mothers. I find evidence that for blacks, the lack of two parents in the household throughout childhood does indeed hamper upward mobility. However, patterns in downward mobility are unaffected by family structure for either blacks or whites. Importantly, the negative effects of single motherhood on blacks are only identified in the SIPP, where the entire marital history during the child's life is available. This highlights the importance of access to data on family structure over long periods rather than a single snapshot at one point in time. I also find that black–white gaps in both upward and downward mobility are significantly smaller for those who have completed 16 years of schooling.⁸

In many ways, this work is complementary to the recent study by Chetty et al. (2014) that has deservedly received a great deal of media attention. Chetty et al.

used very large samples of tax records to construct measures of intergenerational mobility at a very detailed level of geography.⁹ They then showed how differences in intergenerational mobility across places vary with other aggregate measures, such as the level of segregation or family structure. However, their tax data do not include basic individual characteristics, such as race or education. Therefore, they are unable to show how intergenerational mobility differs by race, which is the first key focus of this article.¹⁰ In addition, they cannot include *individual*-level variables, such as parent education, marital status, wealth, or children's test scores, in order to explain mobility differences, which is the second key focus of this article.

Finally, I should also note that the focus of this article is on *relative* mobility across generations and that the measures are relevant for answering questions concerning the progress of blacks relative to whites. It may also be interesting to consider measures of *absolute* mobility, but that is not the focus of this article.

Measures of mobility

Transition probabilities

The upward transition probability (hereafter UTP) used in this analysis is the probability that the child's income percentile (Y_1) exceeds a given percentile, s , in the child's income distribution by an amount τ , conditional on the parent's income percentile (Y_0) being at or below s in the parent's income distribution:

$$1) \quad UTP_{\tau,s} = \Pr(Y_1 > s + \tau \mid Y_0 \leq s).$$

For example, in a simple case where $\tau = 0$ and $s = 0.2$, the upward transition probability ($UTP_{0,0.2}$) would represent the probability that the child exceeded the bottom quintile in the child's generation, conditional on parent income being in the bottom quintile of the parent generation.¹¹ The empirical analysis of upward transition probabilities will vary s in increments of 10 percentiles throughout the bottom half of the distribution (that is, 10, 20, ..., 50). Therefore, as s increases, each successive sample will add more families to the already existing sample. For example, when $s = 0.1$, only families in the bottom decile of the income distribution will be included. When $s = 0.2$, the sample will now include families in the bottom quintile of the income distribution, so that families in the bottom decile are common to both samples but families who are between the 11th and 20th percentiles are now added. This approach and the use of τ are helpful for making comparisons with the directional mobility estimator that I will introduce shortly. I will also show results

that use non-overlapping percentile *intervals* of the parent income distribution (for example, $s \leq 10$ th percentile, 10 th percentile $> s \leq 20$ th percentile ... 40 th percentile $> s \leq 50$ th percentile). Although in principle the interval-based estimates might be more transparent in pinpointing mobility differences at different points in the distribution, unless one has much larger samples, the results are also much noisier than those from using the cumulative samples.

It is straightforward to see that this estimator can be modified to measure downward transition probabilities by altering the inequality signs:

$$2) \quad DTP_{\tau,s} = \Pr(Y_1 \leq s + \tau \mid Y_0 > s).$$

In this case, I vary s from 50 to 90. I also consider intervals such as the highest decile: 90th percentile $< s \leq 100$ th percentile, next highest decile: 80th percentile $< s \leq 90$ th percentile, ..., 50th percentile $< s \leq 60$ th percentile.

Bhattacharya and Mazumder (2011) show how the transition probability can be estimated conditional on continuous explanatory variables using nonparametric regression techniques and demonstrate that bootstrapping is a valid approach for calculating the appropriate standard errors.¹² Using this methodology one can, for example, estimate the difference in transition probabilities between blacks and whites while controlling for the effects of children's test scores and determine whether these differences are statistically significant.

Directional rank mobility

Following Bhattacharya and Mazumder (2011), I use a measure of upward rank mobility (URM) that estimates the likelihood that an individual will surpass their parent's place in the distribution by a given amount, conditional on their parents being at or below a given percentile:

$$3) \quad URM_{\tau,s} = \Pr(Y_1 - Y_0 > \tau \mid Y_0 \leq s).$$

In the simple case where $\tau = 0$, this is simply the probability that the child exceeds the parent's place in the distribution. As with the UTP measure, positive values of τ enable one to measure the *amount* of the gain in percentiles across generations. Results will be shown for a range of values for τ and also as s is progressively increased. Bhattacharya and Mazumder show that the URM measure can also be estimated conditional on continuous covariates using nonparametric regressions.

Similarly, one can construct a measure of downward rank mobility (DRM) using an analogous approach:

$$4) \quad DRM_{\tau,s} = \Pr(Y_0 - Y_1 > \tau \mid Y_0 \geq s).$$

Comparison of transition probabilities and directional rank mobility

One criticism of transition probabilities is that they require using arbitrarily chosen cutoffs such as the 20th percentile. In contrast, the directional rank mobility measures simply compare the child's rank to the parent's rank rather than to an arbitrarily chosen quantile.¹³ In other respects, however, neither estimator is perfect, as discussed by Bhattacharya and Mazumder (2011). Therefore, it seems reasonable to consider both measures and to examine a range of estimates. As I show next, the DRM appears to be robust to the differences across data sets.

Data

NLSY79

The first source of data I use is the *National Longitudinal Survey of Youth 1979* cohort (NLSY79), a data set that has several attractive features. Most notably, there is a very large sample of more than 6,000 individuals for whom we know both family income in adolescence (1978–80) and various economic outcomes as adults (1997–2005).

The NLSY79 began with a sample of individuals who were between the ages of 14 and 21 as of January 1, 1979, and who have since been tracked through adulthood. The NLSY79 conducted annual interviews until 1994 and has since shifted to biennial surveys. The analysis is restricted to the sample of youth who were living at home with their parents during the first three years of the survey and for whom family income was directly reported by the parents in any of these years. Respondents also must have stayed in the sample to adulthood and been interviewed in one of the surveys beginning with 1998 and ending in 2006.¹⁴ The final sample includes 3,440 men and 3,250 women.

The measures of mobility utilize data on the family income of the children during the years 1997, 1999, 2001, 2003, and 2005, when sample members were between the ages of 33 and 48. The measures of permanent family income are constructed for each generation by using multiyear averages using *any* available years of data. Years of zero income are included in the averages. Family income is converted into 2004 dollars using the headline Consumer Price Index CPI series.

A nice feature of the NLSY79 is that it also includes a rich set of explanatory variables pertaining to the children. Measures of human capital include

completed years of education and scores on the Armed Services Vocational Aptitude Battery test (ASVAB), which was given to all NLSY respondents. I will focus on the composite AFQT score, which is used as a screening device by the military and has been used in many previous economic studies.

SIPP–SSA

The second data source pools the 1984, 1990, 1991, 1992, and 1993 panels of the *Survey of Income and Program Participation* (SIPP) matched to administrative earnings records maintained by the Social Security Administration (SSA).¹⁵ The Census Bureau attempted to collect the social security numbers of all individuals in the surveys and they were subsequently matched to SSA administrative databases of summary earnings records (SER) and detailed earnings records (DER). Davis and Mazumder (2011) show that the match rates are high for most SIPP panels and that selection does not appear to be a serious concern.

The SER data cover annual earnings both from employers and self-employment over the period from 1951 to 2007. In the SER data, the earnings of individuals who are not covered by the social security system will have their earnings recorded as zero. Further, the SER data are censored at the maximum level of earnings subject to the social security tax. While the DER data are not subject to either of these issues, they are only available from 1978. Further, the DER data used in this article only cover labor market earnings reported on W-2 forms and not self-employment earnings. Therefore, I combine information from both the SER and DER by taking the maximum value of earnings from the two sources in order to have earnings data from both labor market earnings and self-employment, and I only use the data beginning in 1978.¹⁶

In order to maximize the sample size, I use a relatively liberal set of sample selection rules. I start with a sample of white or black males who were living with their parents at the time of the SIPP and who were no older than 25.¹⁷ I also require that the adult earnings of these men are observed when they are at least 21 years old. Sons' earnings are taken over the five years spanning 2003 through 2007, so as to take earnings at as late a stage in the life cycle as possible to minimize life-cycle bias for the younger cohorts. Although years of zero earnings are included in the average, sons must have positive earnings in at least one year to be included. This produces a sample of 16,782 men, who could have been born anytime between 1959 and 1982 and are observed as adults between the ages of 21 and 48.¹⁸

For children who lived with both their mother and their father, both parents' earnings are combined

and averaged over all years between 1978 and 1986 to construct a measure of permanent earnings. For those children who only lived with a single parent at the time of the SIPP, the parent earnings are recorded as the single parent's earnings. To be included in the sample, parents must have had positive earnings in at least one year.

A limitation of the SIPP–SSA data is that there is little information available for the children during their adult years, aside from their administrative earnings records. However, unlike the NLSY, the SIPP–SSA provides a rich set of data on the parents. In this article, I utilize information on the complete marital histories of the parents present at the time of the SIPP.

Comparison of NLSY79 and SIPP–SSA

Table 1 presents summary statistics for each sample. There are a number of potentially important differences between the samples. The NLSY79 sample includes both sons and daughters and uses family income for both generations. Family income is useful as a way of including daughters in the sample and avoiding issues dealing with selective labor force participation. The administrative data in the SIPP–SSA only has earnings and only for the individuals (not the spouse). Since there is no ideal way of dealing with selection of which daughters participate in the labor force, the analysis with the SIPP–SSA only uses sons. The NLSY79 covers individuals born between 1957 and 1964, while the SIPP sample covers those born over a much longer time span, 1959–82.¹⁹ Parent income is measured over just a three-year period (1978 to 1980) in the NLSY79, but over a nine-year period from 1978 to 1986 in the SIPP. All ranks and quantiles used in the NLSY are based on distributions that include individuals who are neither white nor black. The SIPP–SSA data in contrast is restricted to just whites and blacks. Finally, the NLSY will continue to track respondents and collect income data among respondents even if they become incarcerated. The SIPP–SSA data, in contrast, is confined to the civilian noninstitutionalized population.

Unconditional estimates of intergenerational mobility

Upward transition probabilities (UTP)

The race-specific estimates of upward transition probabilities from both data sets are plotted in figure 1.²⁰ The x-axis varies the sample used based on the percentile range of family income in the parent generation, while the y-axis shows the transition probability that income of children from these families surpassed this range. The blue lines show the estimates for whites, while the red lines show the estimates for blacks. The green lines plot the difference in the probabilities by race, along with standard error bands.²¹ The solid lines

show the estimates using the NLSY and the dashed lines use the SIPP–SSA sample.

I begin by discussing the results using the NLSY. Among white men and women (solid blue line) whose parents' income was at or below the 10th percentile, 84 percent exceed the 10th percentile as adults. As we move to the right and gradually increase the percentile range of family income, the upward transition probabilities fall. For example, among whites starting below the 40th percentile in the parent generation only 54 percent exceed the 40th percentiles as adults. In all cases, the comparable UTP estimates are much lower among blacks (solid red line). For example, among blacks starting in the bottom decile, only 65 percent exceed the bottom decile as adults, a 19 percentage point difference compared with whites. The black–white gap in the probability of rising out of the bottom quintile (solid green line) is even higher at 27 percent.

The SIPP–SSA sample consists only of sons, includes only blacks and whites, includes many more recent cohorts, and uses administrative earnings data rather than family income. Despite these different concepts and measures, the UTP estimates are very similar to those using the NLSY. The general pattern of large and statistically significant differences in point estimates is also evident in the SIPP–SSA data. The fact that the key findings are so similar across the data sets is advantageous, since each data set has its own exclusive set of explanatory variables.

Downward transition probabilities (DTP)

Figure 2 (p. 8) plots an analogous set of downward transition probabilities. Using either data set, I find that blacks are more downwardly mobile. This is most evident when the sample includes a broad range of the upper income distribution in the parent generation. For example, about 60 percent of blacks whose parents were in the top half of the income distribution fall below the 50th percentile in the subsequent generation. The analogous figure for whites is 36 percent.²²

Upward rank mobility (URM)

Figure 3 (p. 9) plots the estimates of upward rank mobility based on equation 3. As might be expected, the rates of upward mobility using the URM are somewhat higher than for the UTP. For example, using the NLSY I find that 75 percent of blacks whose parents were below the 20th percentile surpass their parents' percentile in the family income distribution. In contrast, only 48 percent of this same subsample exceed the 20th percentile, implying that although about 37 percent of blacks starting in the bottom quintile exceed their parents' percentile but do not transition out of the bottom quintile. For whites, the difference in upward mobility

TABLE 1

Summary statistics

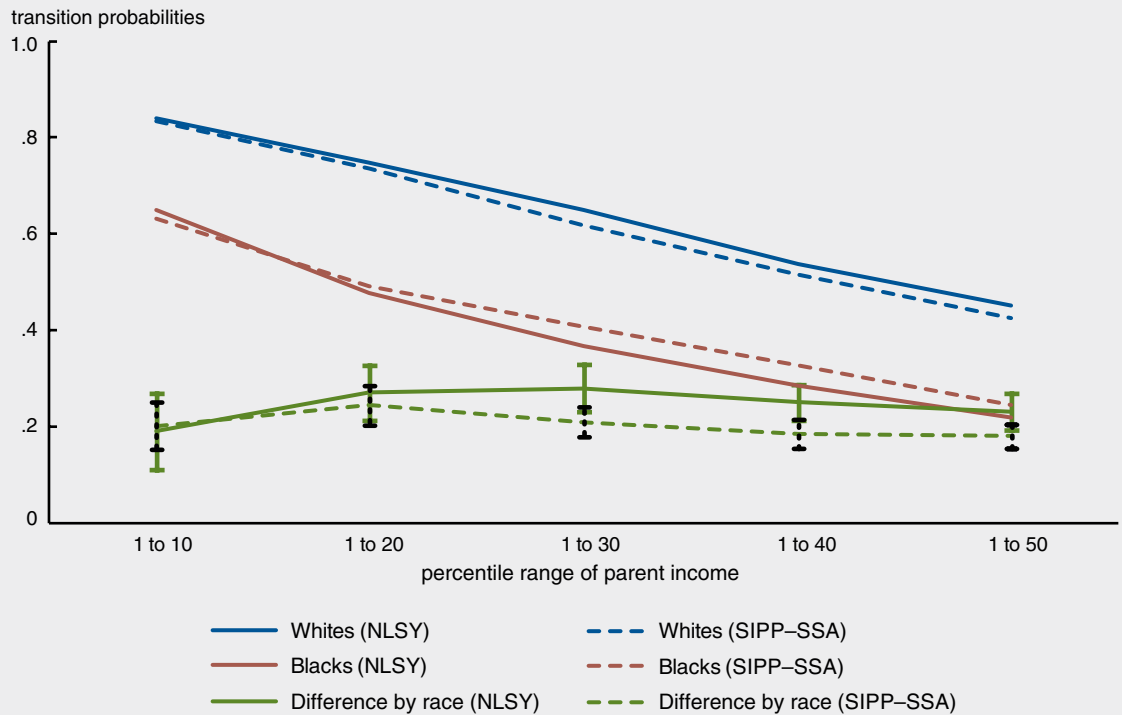
	All			Whites			Blacks		
	Number of observations	Mean	Standard deviation	Number of observations	Mean	Standard deviation	Number of observations	Mean	Standard deviation
Panel A: NLSY79									
Family income (1997–2005)	6,690	69,395	58,953	3,205	76,284	61,316	2,143	42,289	39,070
Child's age in 2001	6,690	39.1	2.2	3,205	39.1	2.2	2,143	39.2	2.2
Education	6,673	13.0	2.3	3,199	13.2	2.3	2,136	12.4	2.1
AFQT	6,432	46.0	28.5	3,080	52.5	27.0	2,082	21.6	19.8
Parent income (1978–80)	6,690	57,760	36,299	3,205	64,354	35,965	2,143	33,743	26,725
Single mother at age 14	6,690	0.13	0.33	3,205	0.08	0.27	2,143	0.3	0.5
Panel B: SIPP–SSA									
Son's log earnings	16,782	10.14	1.07	14,757	10.23	1.00	2,025	9.48	1.32
Son's age in 2005	16,782	30.93	5.69	14,757	30.97	5.71	2,025	30.66	5.55
Single parent	16,782	0.21	0.41	14,757	0.17	0.38	2,025	0.53	0.50
1984 panel	16,782	0.26	0.44	14,757	0.25	0.43	2,025	0.27	0.45
1990 panel	16,782	0.23	0.42	14,757	0.23	0.42	2,025	0.23	0.42
1991 panel	16,782	0.14	0.35	14,757	0.15	0.35	2,025	0.12	0.33
1992 panel	16,782	0.20	0.40	14,757	0.20	0.40	2,025	0.19	0.40
1993 panel	16,782	0.18	0.38	14,757	0.18	0.38	2,025	0.18	0.38
Parent log earnings	16,782	10.32	1.06	14,757	10.42	1.00	2,025	9.63	1.26
Father's age in 1982	15,354	35.72	8.85	13,467	36.09	8.75	1,887	33.11	9.14

Notes: NLSY79 is the U.S. Bureau of Labor Statistics' *National Longitudinal Survey of Youth 1979*. AFQT is the Armed Forces Qualification Test. SIPP–SSA matches data from the U.S. Census Bureau's *Survey of Income and Program Participation* to administrative earnings records from the Social Security Administration.

Sources: Author's calculations based on data from U.S. Bureau of Labor Statistics, U.S. Census Bureau, and U.S. Social Security Administration.

FIGURE 1

Upward transition probabilities by race using cumulative samples ($\tau = 0$)



Notes: NLSY is the U.S. Bureau of Labor Statistics' *National Longitudinal Survey of Youth*. SIPP-SSA matches data from the U.S. Census Bureau's *Survey of Income and Program Participation* to administrative earnings records from the Social Security Administration.

Sources: Author's calculations based on data from U.S. Bureau of Labor Statistics, U.S. Census Bureau, and U.S. Social Security Administration.

between the two measures is much smaller. Therefore, the URM estimator (for $\tau = 0$) shows a much smaller black–white gap that fluctuates around 0.1 across the samples in the bottom half of the income distribution of parents. Interestingly, figure 3 shows that the estimates based on the URM are nearly identical across the two data sets, which suggests that it is an especially robust measure.

The finding of a smaller black–white gap using the URM rather than the UTP measure is sensitive to the chosen value of τ . For example, if τ is set to 0.2, then the black–white differences in upward rank mobility rise considerably. For example, among men and women in the NLSY whose parents' family income placed them in the bottom quintile, blacks are nearly 25 percent less likely to surpass their parents' rank by 20 percentiles or more. Using the SIPP-SSA data, the analogous black–white difference for men is 21 percent. Figure 4 (p. 10) plots the full set of estimates for the case where τ equals 0.2.

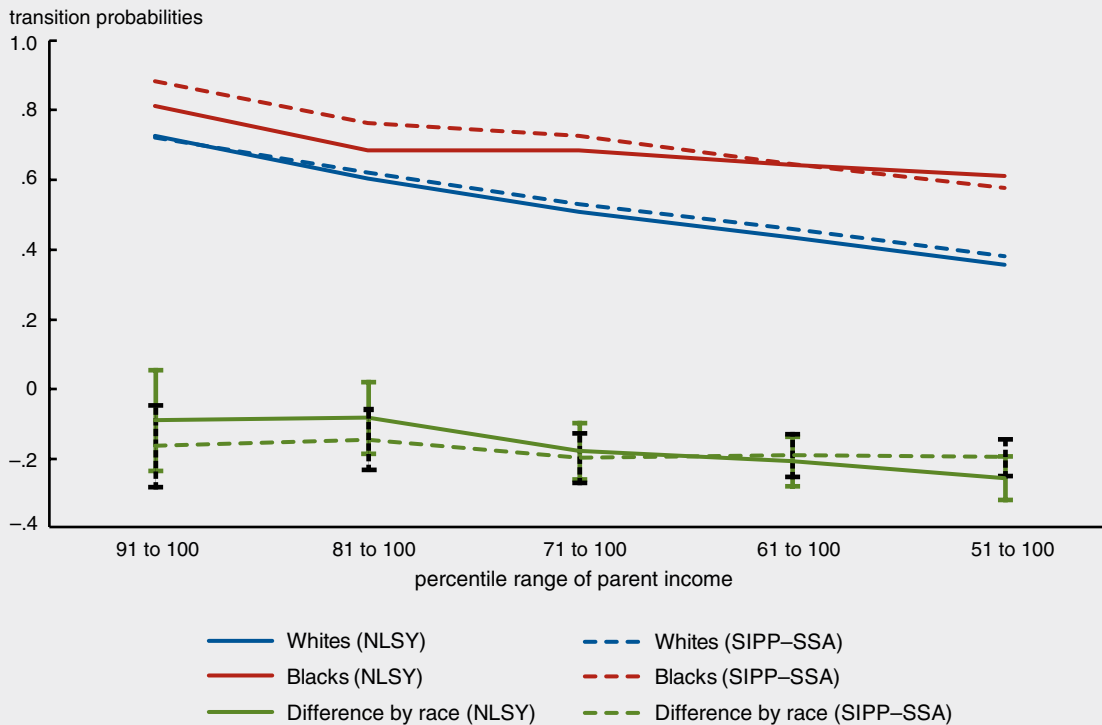
Downward rank mobility (DRM)

Estimates of downward rank mobility are shown in figure 5 (p. 11). Using the simple measure ($\tau = 0$), I again observe higher rates of downward mobility among blacks than whites that is less pronounced in the top two deciles. The estimates of DRM are higher, however, than those of DTP. For example, among whites in the NLSY sample whose parents' income was in the top half of the income distribution, 69 percent were in a lower rank in the distribution than their parents, even though only 36 percent fell below the median. For blacks starting in the top half of the income distribution, 79 percent fell below their parents and 61 percent also dropped below the median. Therefore, the estimates of the black–white gap in downward mobility using the baseline DRM measure are considerably smaller in absolute value than the analogous estimates using DTP.

The comparison of the two downward mobility measures is also sensitive to the choice of τ . For example, if we consider the probability of those in the top half of the distribution falling 20 percentiles or more, the black–white gap is 18 percent in the NLSY

FIGURE 2

Downward transition probabilities by race using cumulative samples ($\tau = 0$)



Notes: NLSY is the U.S. Bureau of Labor Statistics' *National Longitudinal Survey of Youth*. SIPP-SSA matches data from the U.S. Census Bureau's *Survey of Income and Program Participation* to administrative earnings records from the Social Security Administration. Sources: Author's calculations based on data from U.S. Bureau of Labor Statistics, U.S. Census Bureau, and U.S. Social Security Administration.

and 14 percent in the SIPP-SSA. The racial differences in DRM when $\tau = 0.2$ show somewhat different patterns across the income distribution depending on the data set used, as shown in figure 6 (p. 12). For example, the black-white difference in the probability of falling 20 percentiles below one's parents among those who start in the top decile is only 7 percent in the NLSY, but it is 23 percent in the SIPP-SSA. This likely reflects differences that are due to the relevant concept of income. Compared with whites, blacks starting in the top decile are more likely to suffer larger drops in their earnings rank than in their family income rank.

Upward mobility using interval-based samples

The results presented so far have used samples that have progressively expanded the range of families, starting from either the bottom or the top of the parent income distribution. It might also be interesting to see the results within much narrower percentile ranges to see how mobility changes across the distribution. Figure 7 (p. 13) shows estimates of UTP and URM using interval-based samples from deciles in the bottom half of the income

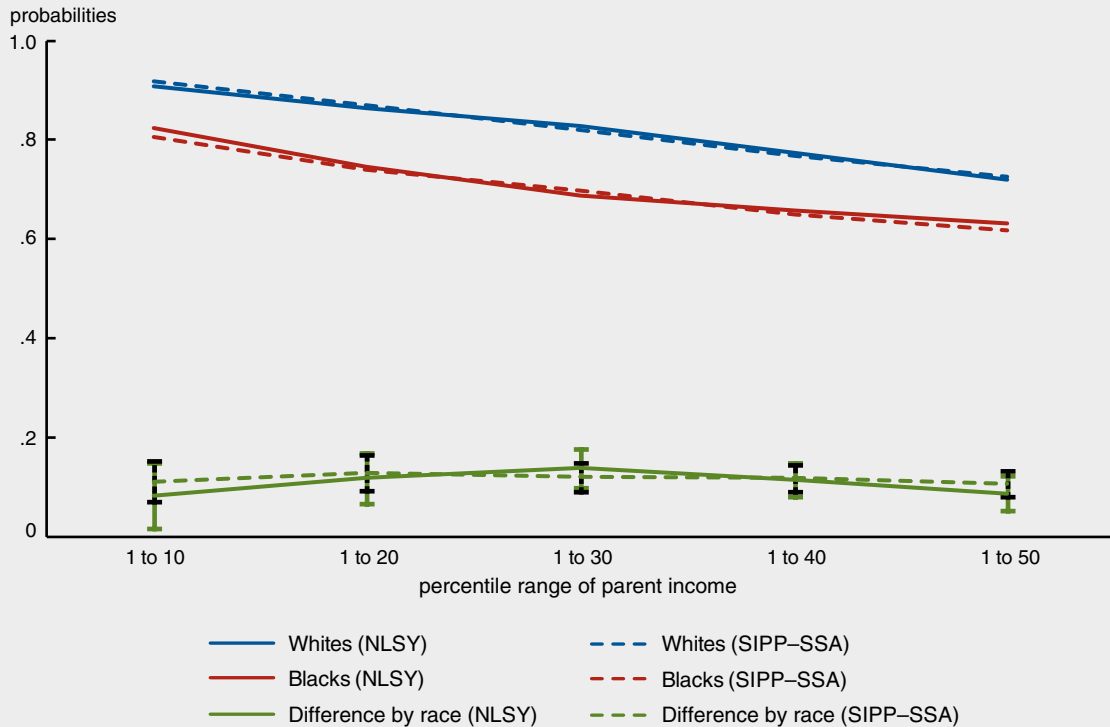
distribution.²³ For most of the bottom half of the income distribution, the racial differences in upward mobility are consistently between 20 and 30 percent. The greater similarity between the UTP and URM estimates is not surprising since, as the interval range becomes smaller, the two estimates will converge.²⁴

Implications of transition probabilities on the steady-state distributions by race

The transition matrix of movements across quintiles of the income distribution over generations for blacks and whites based on the SIPP-SSA are shown in table 2 (p. 14). The general patterns concerning racial differences in upward and downward mobility are again evident. For example, more than 50 percent of blacks who start in the bottom quintile in the parent generation remain there in the child generation, but only 26 percent of whites remain in the bottom quintile in both generations. Whites are less likely to transition out of the top quintile compared with blacks, suggesting a distribution that may not be exhibiting racial convergence. Assuming that these specific probabilities are a

FIGURE 3

Upward rank mobility by race using cumulative samples ($\tau = 0$)



Notes: NLSY is the U.S. Bureau of Labor Statistics' *National Longitudinal Survey of Youth*. SIPP-SSA matches data from the U.S. Census Bureau's *Survey of Income and Program Participation* to administrative earnings records from the Social Security Administration.
Sources: Author's calculations based on data from U.S. Bureau of Labor Statistics, U.S. Census Bureau, and U.S. Social Security Administration.

permanent feature of the U.S. economy, they can be used to calculate an implied steady-state distribution using standard matrix algebra methods for solving Markov chains. The results show, for example, that in the steady state, 39 percent of blacks would occupy the bottom quintile of the income distribution and only 8 percent would be in the top quintile.²⁵ This finding suggests that rather than convergence, blacks will remain perpetually disadvantaged in American society if mobility patterns continue to evolve as they have for the cohorts studied in this article. As I discuss next, however, there are potential levers through which policy could address this problem.

Estimates of intergenerational mobility controlling for explanatory variables

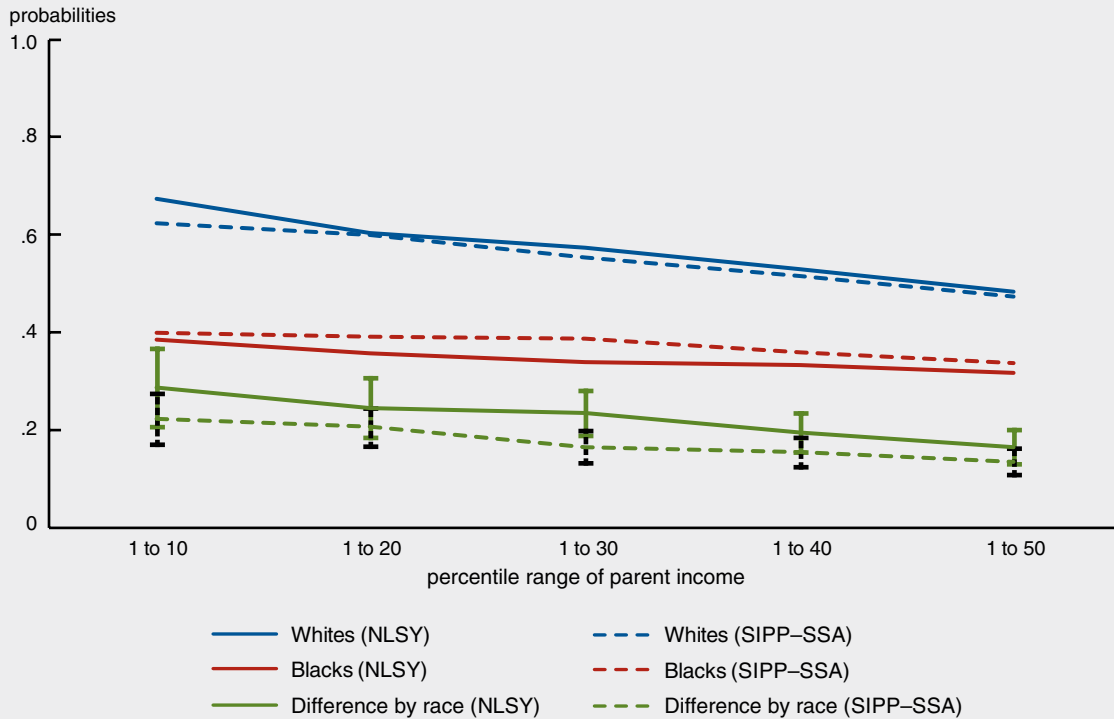
Ideally, we would like to understand the causal factors that explain the observed patterns of intergenerational mobility and the possible implications for policies designed to address racial differences in mobility. For example, we might like to know whether a particular schooling intervention such as smaller classes

might improve students' prospects for upward mobility and whether this could reduce the racial gap in upward mobility. Such a study would not only require a convincing research design to address standard concerns about endogeneity bias—for example, to ensure that the intervention was not directed at individuals who would have succeeded even in the absence of the intervention—but would also likely require high-quality income data spanning multiple years of adulthood for *two generations of the same set of families*. Instead, like the recent work by Chetty et al. (2014), which also does not attempt to estimate causal effects, I opt for a more modest goal and conduct a descriptive analysis to explore how the inclusion of other available explanatory variables affects the racial differences in upward and downward intergenerational mobility. Such a “first pass” analysis may yield useful clues about which factors are potentially important.

To simplify the analysis, I focus only on transition probabilities.²⁶ For a representative measure of upward mobility, I use the transition probability of moving out of the bottom quintile. For downward mobility,

FIGURE 4

Upward rank mobility by race using cumulative samples ($\tau = 0.2$)



Notes: NLSY is the U.S. Bureau of Labor Statistics' *National Longitudinal Survey of Youth*. SIPP-SSA matches data from the U.S. Census Bureau's *Survey of Income and Program Participation* to administrative earnings records from the Social Security Administration. Sources: Author's calculations based on data from U.S. Bureau of Labor Statistics, U.S. Census Bureau, and U.S. Social Security Administration.

I focus only on the probability of moving out of the top half of the income distribution over the course of a generation. I first consider the effects of two explanatory variables from the NLSY, the child's education level and the child's test score. I then turn to a measure of family structure from the SIPP-SSA data, which compares children who have ever lived with just one parent with children who have always lived with two parents.

For the first two measures, I use a statistical technique that shows how each explanatory variable affects whether a child exceeds the bottom quintile as an adult and how this association changes at different values of the explanatory variable.²⁷ I produce a series of plots of the upward transition probability at each value of the explanatory variable for each racial group. In addition, I plot the black-white difference, along with 95 percent confidence bands. Finally, as a point of reference, I include the baseline transition probabilities that do not account for the explanatory variables in lightly shaded horizontal lines. An explanatory variable with a positive association with upward mobility

will produce an upward sloped line and may reduce the black-white gap in upward mobility.

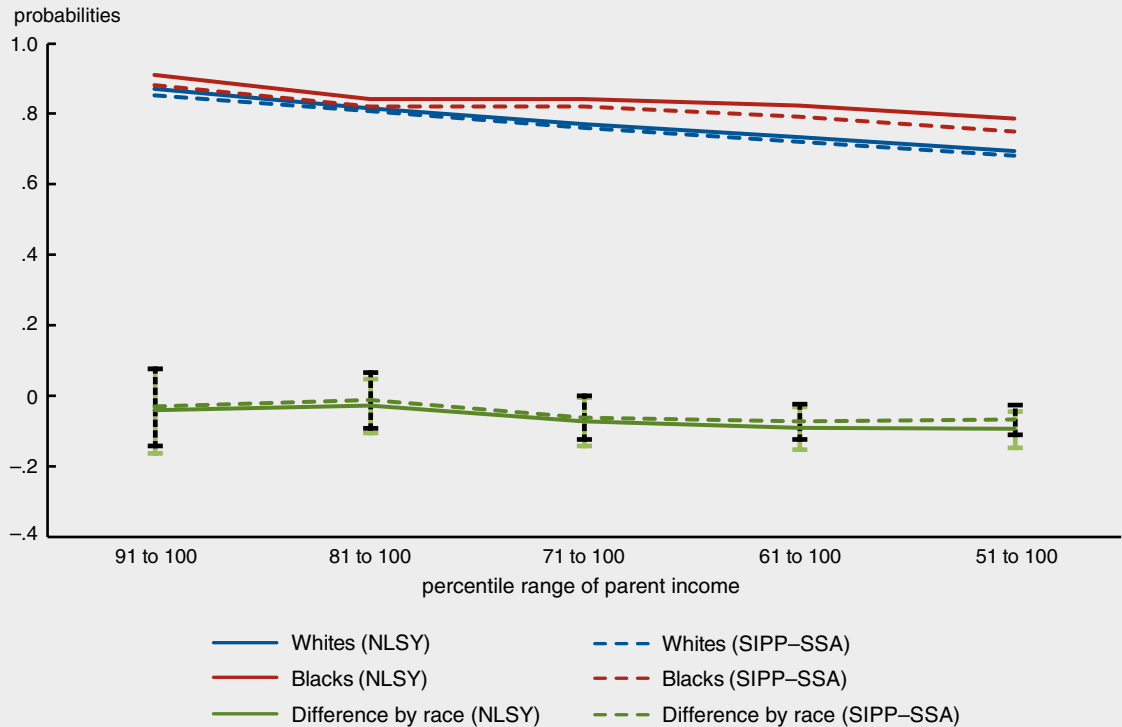
Effects of education

The left-hand-side panels in figure 8 (p. 15) show the results for upward mobility and the right-hand-side panels show the plots for downward mobility. Panel A shows that, as would be expected, more years of completed schooling are associated with a greater likelihood of rising out of the bottom quintile. For example, 89 percent of whites with exactly 16 years of schooling will escape the bottom quintile, compared with 75 percent of whites with exactly 12 years of schooling. For blacks, rates of upward mobility are extremely low for those with less than a high school education but begin to rise sharply for those who attain more than a high school education. For example, for blacks with exactly ten years of schooling, only 28 percent will transition out of the bottom quintile, compared with 69 percent of blacks with exactly 14 years of schooling.

With respect to the *racial gap* in upward mobility, controlling for education provides something of a mixed

FIGURE 5

Downward rank mobility by race using cumulative samples ($\tau = 0$)



Notes: NLSY is the U.S. Bureau of Labor Statistics' *National Longitudinal Survey of Youth*. SIPP-SSA matches data from the U.S. Census Bureau's *Survey of Income and Program Participation* to administrative earnings records from the Social Security Administration.
Sources: Author's calculations based on data from U.S. Bureau of Labor Statistics, U.S. Census Bureau, and U.S. Social Security Administration.

picture. On one hand, the point estimate for the racial gap in upward mobility among those with less than a high school education is actually higher than the estimate when education is not controlled for, although this difference is not statistically significant. On the other hand, the racial gap narrows sharply with additional years of post-secondary education. Indeed, among those with 16 years of schooling, the racial gap in upward mobility gap is essentially closed. Nevertheless, the racial gap is still quite large among those with some post-secondary education who have not completed college. For example, the black–white gap among those with 14 years of schooling is still sizable at 16 percent. Given that only 17 percent of blacks in the NLSY attained more than 14 years of schooling, this suggests that *marginal* improvements in educational attainment may not do a great deal to improve the overall upward mobility prospects of blacks.

The effects of education on downward mobility are shown in panel B of figure 8. As expected, the lines slope downward. Since I am sampling only families with parents in the top half of the income distribution,

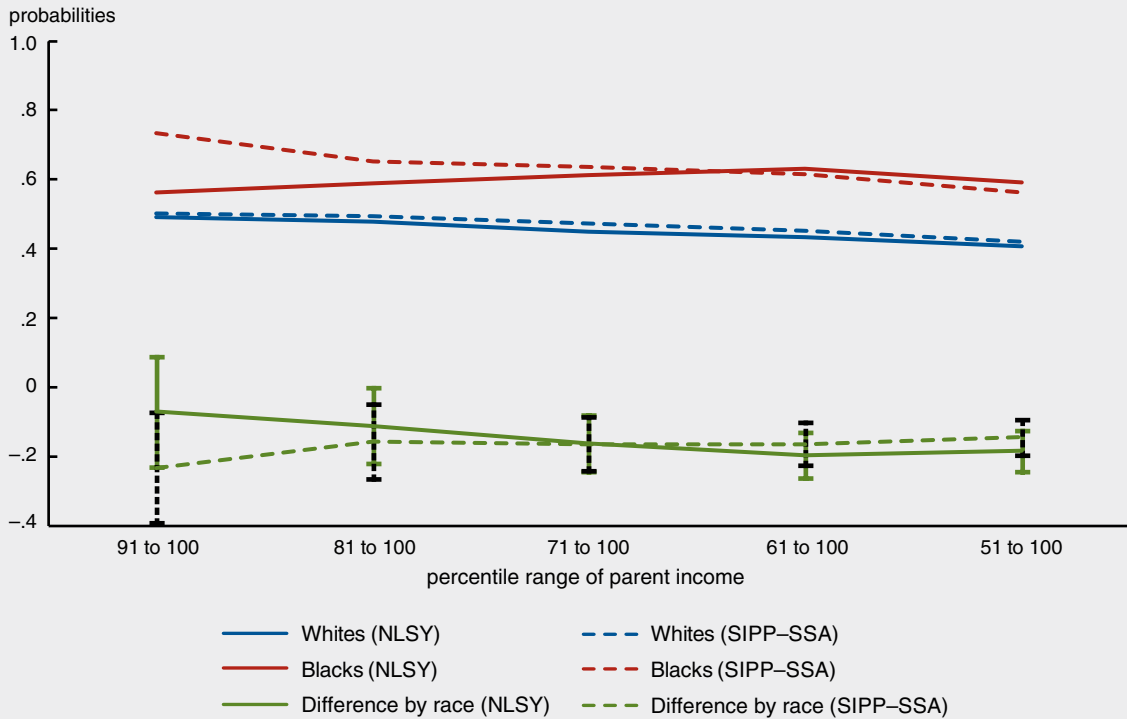
the samples of individuals with less than a high school education are relatively small, so the estimates for these values are especially noisy. As was the case with upward mobility, additional years of post-secondary schooling are associated with a reduction in the racial gap in downward mobility. Among those with 16 years of schooling, the black–white gap is reduced to just 14 percentage points, and it disappears entirely among those with 17 years or more of schooling.

Effects of test scores

The effects of including one's AFQT score on rates of upward mobility are shown in panel C of figure 8. Here, the results provide a relatively clean and compelling story. For both blacks and whites, upward mobility rises with AFQT scores in a fairly similar fashion. There are especially sharp gains in upward mobility associated with increases in test scores at the low end of the AFQT distribution. Upward mobility continues to rise at a somewhat slower but still strong rate in the middle and in the upper half of the AFQT distribution. Remarkably, the lines for blacks

FIGURE 6

Downward rank mobility by race using cumulative samples ($\tau = 0.2$)



Notes: NLSY is the U.S. Bureau of Labor Statistics' *National Longitudinal Survey of Youth*. SIPP-SSA matches data from the U.S. Census Bureau's *Survey of Income and Program Participation* to administrative earnings records from the Social Security Administration. Sources: Author's calculations based on data from U.S. Bureau of Labor Statistics, U.S. Census Bureau, and U.S. Social Security Administration.

and whites are relatively close throughout the AFQT distribution. For example, the black–white gap in moving out of the bottom quintile is only 5.2 percentage points for those with median AFQT scores, compared with the unconditional gap of 27 percentage points. This suggests that cognitive skills measured at adolescence can “account” for much of the black–white difference in upward mobility. This result echoes previous findings by Neal and Johnson (1996) and Cameron and Heckman (2001), who have also found that AFQT scores can account for much of the racial gap in adult earnings and college enrollment rates. As with these aforementioned studies, I interpret this finding as reflecting the cumulative effect of a broad range of family background influences rather than reflecting only innate differences.²⁸

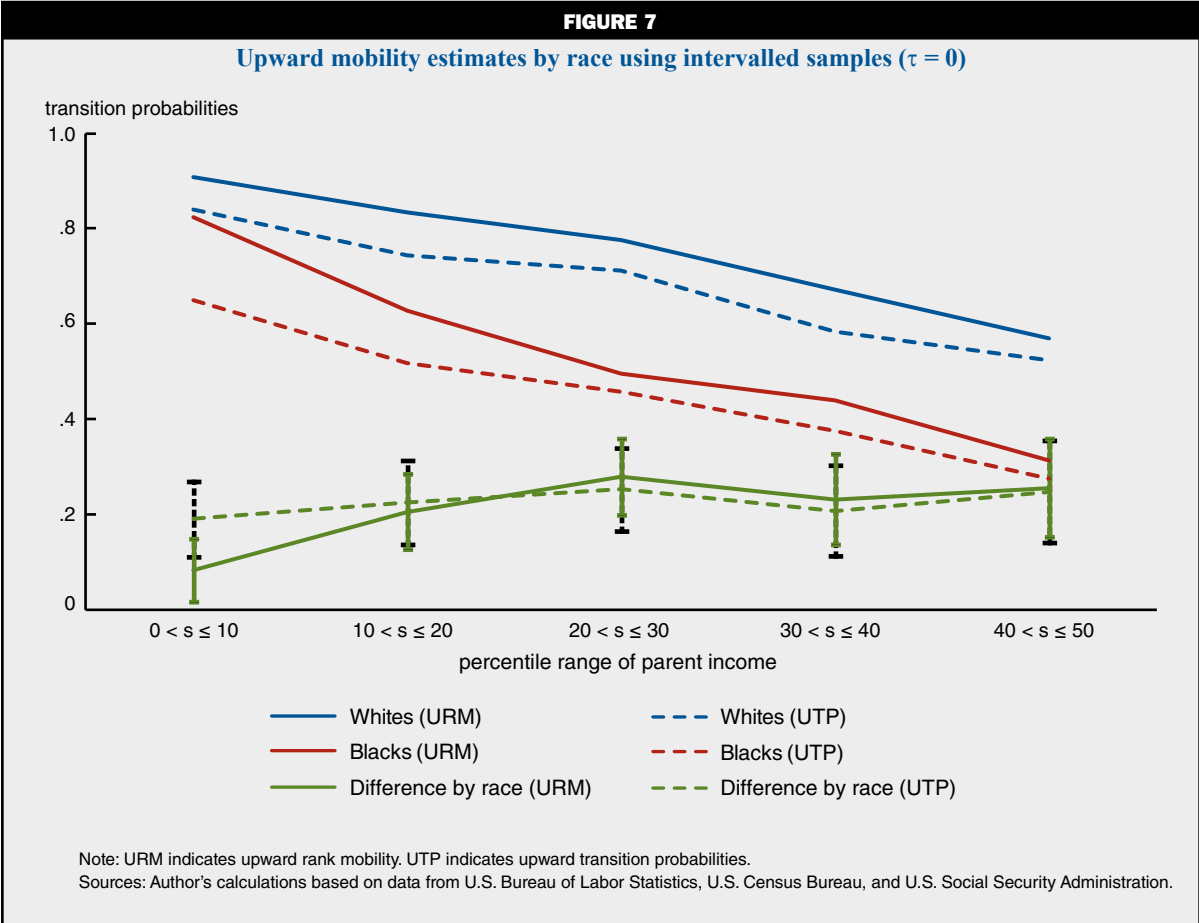
The effects of AFQT scores on downward mobility (panel D of figure 8) are also quite striking. The lines for whites and blacks converge quite a bit and for a broad swath of the AFQT distribution, the racial gap is below 10 percentage points and is not statistically different from 0. Therefore, as was the case with upward

mobility, test scores during adolescence are strongly associated with rates of downward mobility.

Effects of family structure

To understand the role of family structure, I use data from the SIPP-SSA where I have data on family structure throughout the child’s life.²⁹ For whites, upward mobility out of the bottom quintile actually declines slightly from 0.75 (0.02) for those who ever lived with just one parent to 0.71 (0.02) for those who always lived with two parents. For blacks, however, we see an increase in the transition probability from 0.47 (0.02) to 0.58 (0.02). The black–white gap declines from 0.28 (0.02) to 0.13 (0.06). This 15 percentage point improvement in upward mobility for blacks relative to whites is statistically significant at the 5 percent level. On the other hand, I find virtually no difference in downward mobility by whether sons always lived with two parents or not, for either blacks or whites.

It is worth noting that Chetty et al. (2014) show that the strongest predictor of intergenerational mobility differences between commuting zones is the fraction



of families in the commuting zone headed by single mothers. However, Chetty et al. do not show the direct effect of having a single parent on intergenerational mobility differences at the individual level.

Conclusion

One can potentially gain insight into the dynamics of the racial gap in economic status in the United States and better understand how long it will take before there is complete convergence by examining rates of intergenerational income mobility. Using measures that are suited to describing racial differences in intergenerational mobility with respect to a common distribution, I find dramatically lower rates of upward mobility from the bottom of the income distribution and dramatically higher rates of downward mobility from the top of the distribution among blacks born between the late 1950s and early 1980s.

In combination the estimates imply a steady-state income distribution that shows no racial convergence. In other words, if future generations of white and black Americans experience the same rates of intergenerational

mobility as these cohorts, we should expect to see that blacks on average would not make any relative progress. While these results are provocative, they stand in contrast to other epochs in which blacks have made steady progress in reducing racial differentials. These findings, therefore, should not be taken to imply that racial progress is infeasible but rather to highlight what current trends, if they were to continue, would suggest about the future.

These results also underscore the importance of understanding what kinds of policies can potentially foster greater upward mobility and reduce downward mobility for blacks. While this article does not seek to identify definitive causal channels, the use of statistical models that include explanatory variables suggests a few potential areas for policymakers to consider. Similar to previous studies that have looked at static gaps in black–white earnings and college-going rates using NLSY data (for example, Neal and Johnson, 1996; Cameron and Heckman, 2001), it is apparent that the cumulative effects of a variety of influences that affect cognitive ability by adolescence play a critical role in

TABLE 2

Transition matrices by race using SIPP–SSA sample

Parents' income quintile	Child's income quintile				
	1	2	3	4	5
Panel A: Whites					
1	0.263 (0.008) 2,510	0.267 (0.007) 2,510	0.208 (0.006) 2,510	0.159 (0.005) 2,510	0.103 (0.005) 2,510
2	0.205 (0.009) 2,815	0.239 (0.008) 2,815	0.219 (0.007) 2,815	0.204 (0.006) 2,815	0.133 (0.005) 2,815
3	0.156 (0.007) 2,999	0.203 (0.007) 2,999	0.236 (0.007) 2,999	0.223 (0.006) 2,999	0.182 (0.006) 2,999
4	0.147 (0.007) 3,165	0.162 (0.006) 3,165	0.206 (0.007) 3,165	0.234 (0.006) 3,165	0.250 (0.006) 3,165
5	0.113 (0.006) 3,268	0.136 (0.006) 3,268	0.155 (0.006) 3,268	0.217 (0.007) 3,268	0.380 (0.007) 3,268
Panel B: Blacks					
1	0.508 (0.017) 846	0.207 (0.021) 846	0.155 (0.025) 846	0.092 (0.034) 846	0.038 (0.048) 846
2	0.357 (0.013) 541	0.246 (0.020) 541	0.203 (0.023) 541	0.129 (0.028) 541	0.065 (0.041) 541
3	0.341 (0.012) 358	0.212 (0.018) 358	0.176 (0.021) 358	0.190 (0.030) 358	0.081 (0.045) 358
4	0.272 (0.010) 191	0.236 (0.012) 191	0.173 (0.019) 191	0.178 (0.028) 191	0.141 (0.042) 191
5	0.213 (0.007) 89	0.180 (0.011) 89	0.180 (0.015) 89	0.191 (0.026) 89	0.236 (0.048) 89

Notes: SIPP–SSA matches data from the U.S. Census Bureau's *Survey of Income and Program Participation* to administrative earnings records from the Social Security Administration. Both panels use subsamples drawn from a sample of 16,782 men from the SIPP–SSA data and a multiyear average of sons' earnings over 2003–07 and parents' earnings over 1978–86. Bootstrapped standard errors are in parentheses. Sample sizes are shown below the standard errors.

Sources: Author's calculations based on data from U.S. Bureau of Labor Statistics, U.S. Census Bureau, and U.S. Social Security Administration.

accounting for racial differences in upward and downward mobility. A growing literature has shown that black–white differences in test scores, and military test scores in particular, have been narrowed through large-scale policy interventions throughout American history (for example, Chay, Guryan, and Mazumder, 2009; Aaronson and Mazumder, 2011). Other studies (for example, Dobbie and Fryer, 2011) have also shown the potential for modern educational interventions to improve the black–white gap in educational achievement.

Educational attainment also appears to matter for both upward and downward mobility, but the effects of education on reducing racial mobility differentials occur primarily at the margin of acquiring higher education. If racial gaps in college attainment are primarily due to

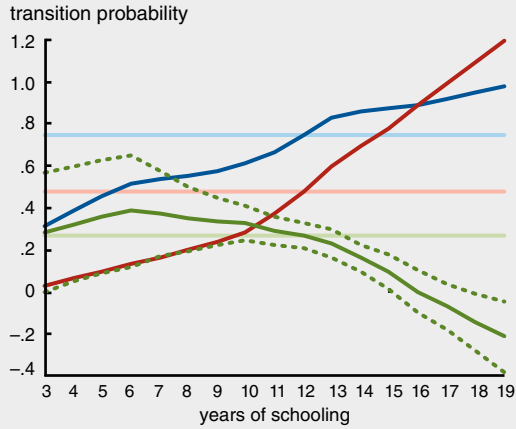
skill differences determined in adolescence (Cameron and Heckman, 2001), then this also points to the importance of interventions earlier in life. Still, there may be some scope for higher education policies that ease credit constraints for families for whom those constraints are binding.

Many commentators have pointed to the prevalence of black children raised by single mothers as a source of racial gaps in economic success. I find supportive evidence that blacks raised in two-parent families throughout childhood experience significantly greater upward mobility. However, family structure appears not to matter for whites or for rates of downward mobility for either blacks or whites. Future research may provide greater insight into these patterns of results.

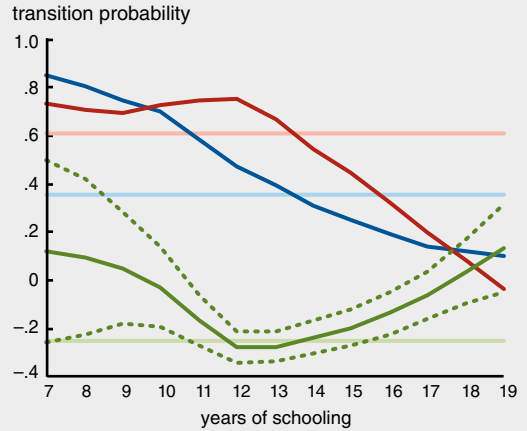
FIGURE 8

Transition probability estimates controlling for explanatory variables

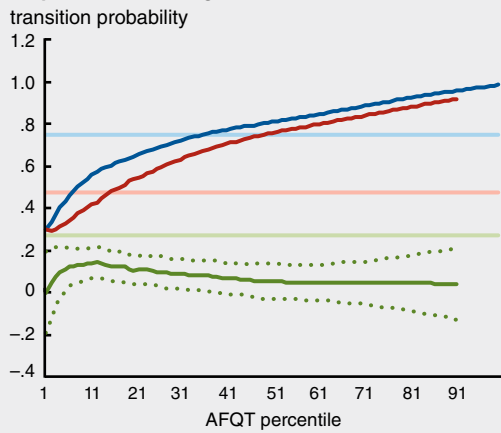
A. Upward transition probability out of bottom quintile controlling for education



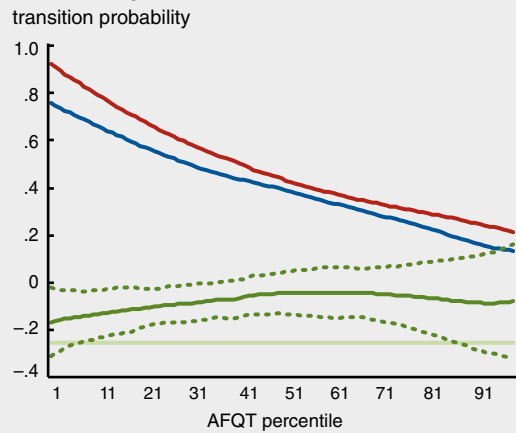
B. Downward transition probability out of top half controlling for education



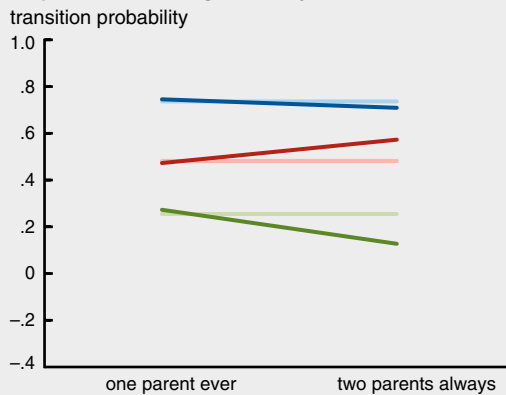
C. Upward transition probability out of bottom quintile controlling for AFQT scores



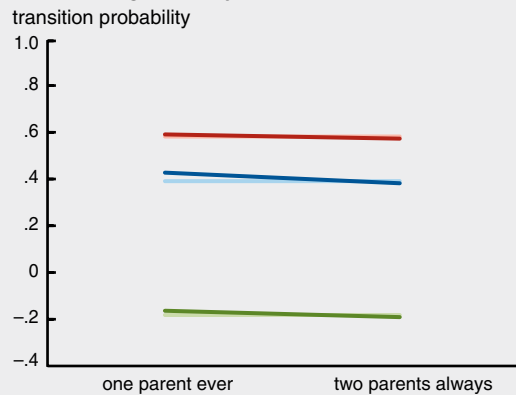
D. Downward transition probability out of top half controlling for AFQT scores



E. Upward transition probability out of bottom quintile controlling for family structure



F. Downward transition probability out of top half controlling for family structure



— Whites
— Blacks
— Whites, unconditional
— Blacks, unconditional
— Difference by race
— Difference by race, unconditional
⋯ 95% confidence interval

Note: AFQT is the Armed Forces Qualification Test.

Sources: Author's calculations based on data from U.S. Bureau of Labor Statistics, U.S. Census Bureau, and U.S. Social Security Administration.

NOTES

¹President Obama highlighted equality of opportunity in an address in 2011. See www.whitehouse.gov/the-press-office/2011/12/06/remarks-president-economy-osawatomic-kansas. Republican leaders have also raised concerns about low economic mobility. See <http://business.time.com/2012/01/05/the-loss-of-upward-mobility-in-the-u-s/>.

²These include Isaacs, Sawhill, and Haskins (2008), Mazumder (2008), and Acs (2011), which were all produced as part of the Pew Economic Mobility Project. Mazumder (2008) uses the NLSY, while the other studies use the PSID.

³In a methodological paper, Bhattacharya and Mazumder (2011) introduced these measures and demonstrated their properties. This article builds upon Bhattacharya and Mazumder in several ways, including adding a second data source that utilizes administrative records; adding daughters' outcomes; considering racial differences in downward mobility; and adding many more explanatory variables to the analysis.

⁴Smith and Welch (1989) show that there was significant convergence in the black–white wage gap from 1940 to 1980 that was due to improvements in black educational attainment and school quality and migration patterns.

⁵This was first found by Bhattacharya and Mazumder (2011). The residual racial gap in upward mobility conditional on AFQT, however, is higher in this study and may be due to the fact that this paper uses children's family income rather than earnings, includes women, and uses income measured at later ages.

⁶A growing literature suggests that black–white differences in test scores can be strongly affected by environmental influences. For example, see Chay, Guryan, and Mazumder (2009) and Aaronson and Mazumder (2011).

⁷There may be other race-specific behavioral differences that can affect the interpretation of economic gaps that adjust only for AFQT scores. Lang and Manove (2011) argue that for signaling reasons, blacks obtain more education than whites conditional on AFQT scores.

⁸In the working paper version of this article (Mazumder, 2011), I show that low levels of parental wealth among blacks also inhibit the prospects for upward mobility.

⁹Chetty et al. (2014) measure intergenerational mobility at the level of “commuting zones,” which are an aggregation of counties that include rural areas.

¹⁰They conduct one exercise using samples that vary in the share of the population that is white (inferred based on geographic residence) in order to show that segregation is associated with reduced upward mobility of whites as well as blacks.

¹¹Many previous papers on intergenerational mobility have used a quintile transition matrix to characterize mobility by showing what proportion of those who start in each quintile end up in each quintile in the subsequent generation. This example would measure 1 minus the probability of remaining in the bottom quintile. A quintile transition matrix is shown in table 2.

¹²Formby, Smith, and Zheng (2004) develop a distribution theory for marginal transition probabilities that can be easily extended to the case of discrete covariates. Unfortunately, for many covariates of interest that are commonly treated as continuous, such as years of schooling or test scores, this is not of much practical value. In order to implement the TP estimator, one must first estimate quantiles of

the income distribution. Since the TP estimates conditional on continuous covariates will involve non-smooth functions of these initially estimated functions, it is technically challenging to show that one can bootstrap the standard errors.

¹³When making comparisons between population subgroups, there is an unambiguous advantage to using the URM. However, Bhattacharya and Mazumder (2011) show that when using the full sample (that is, pooling all subgroups), the URM measure is only meaningful if there is some cutoff, s , used to condition the sample. The choice of s , of course, is likely to be arbitrary. Even in this case, however, children's ranks are still directly compared to their parents' rank as opposed to an arbitrary quantile.

¹⁴The analysis includes individuals from both the cross-sectional representative samples and the supplemental samples (for example, blacks and Hispanics). Following Neal and Johnson (1996) and Cameron and Heckman (2001), I combine the cross-sectional and supplemental samples of blacks and utilize the 1979 sampling weights.

¹⁵This data source is not publicly available. Researchers must apply to obtain the data through the Center for Economic Studies at the U.S. Census Bureau (www.census.gov/ces).

¹⁶For a small set of self-employed individuals whose earnings were above the taxable maximum, this approach understates their true earnings. To address this, I obtained the full DER data (including the non-top-coded self-employed earnings) and redid all of the analysis. I found that using the full DER data has an imperceptible effect on the results (typically only changing estimates at the third decimal place). Since there are procedural difficulties in releasing a second set of statistical results through the Census Bureau disclosure avoidance review process in cases where revised estimates lead the sample size to change by just one or two individuals, and since the current results are virtually identical to the corrected ones, I have opted to show the current results that combine both the SER and DER data.

¹⁷Restricting the sample to whites and blacks avoids implicitly disclosing any information concerning men who are neither white nor black, thereby making it easier to pass Census Bureau disclosure avoidance review. Similarly, the upper age restriction of 25 is not ideal—one might prefer a younger age cutoff, such as 17 or 18, to avoid including men who lived at home into adulthood—but I chose it to make it easier to maximize sample sizes for the purposes of Census Bureau disclosure avoidance review. It is worth noting that in the SIPP individuals residing at college are included in the household. To some degree, this mitigates the concern of having an older age cutoff. In any case, the results are not sensitive to restricting the age cutoff to 18. There is no lower bound on the age when living at home.

¹⁸As I discuss later, the results are not sensitive to requiring sons to be at least 28 years old.

¹⁹Haider and Solon (2006) demonstrate that estimates of intergenerational elasticity can be biased depending on the ages at which the incomes of children and parents are measured. They find that such bias is minimized when income is measured around the age of 40. It is not clear whether a similar bias would arise with respect to the statistical measures utilized here, since they are very different from the regression coefficients analyzed by Haider and Solon. Indeed, the directional rank mobility measures, in particular, seem to be robust to the various measurement differences between the samples. In any case, life-cycle bias is likely to be minimal in the NLSY79 sample, since the mean age of the children in 2001 (the middle year of the sample) is 39, which is close to ideal according to

Haider and Solon. In the SIPP–SSA sample, the mean age of the sons in 2005 (the middle year of the sample) is 31. However, I found very similar results using an older SIPP–SSA sample.

²⁰The underlying estimates and the standard errors are available in tabular form in Mazumder (2011), which is a working paper version of this article.

²¹Owing to the large samples, all of the estimated gaps are highly statistically significant.

²²There is a somewhat notable difference between the two data sets in the degree of downward mobility out of the top decile for blacks. In the NLSY, which uses family income in both generations, 81 percent of black children whose parents were in the top decile fall below the top decile as adults. The comparable figure is 88 percent in the SIPP–SER data, where the income concept is earnings.

²³The UTP estimates are drawn from the NLSY sample, while the URM estimates are drawn from the SIPP–SSA sample.

²⁴This is obvious at the limit, since the probability of exceeding the percentile (URM) of one’s parent(s) and the probability of exceeding any given percentile threshold (UTP) will be identical if the sample is conditioned on the same percentile in each case.

²⁵Further, 22 percent of blacks would be in the second quintile, 17 percent in the third quintile, and 14 percent in the fourth quintile. The shares of whites across the distribution from the bottom to top quintiles is as follows: 17 percent, 20 percent, 20 percent, 21 percent, and 22 percent.

²⁶I found the same general pattern of results using the DRM measures.

²⁷Following Bhattacharya and Mazumder (2011), I use locally weighted regressions and calculate standard errors using the bootstrap method.

²⁸A growing number of studies (Neal and Johnson, 1996; Hansen, Heckman, and Mullen, 2004; Cascio and Lewis, 2006; Chay, Guryan, and Mazumder, 2009; and Aaronson and Mazumder, 2011) have shown that environmental influences can have large effects on military test scores and narrow racial differences.

²⁹The latter category includes those whose parents were ever separated, divorced, or widowed. The sample includes those who were given the marital history topical module in the SIPP and who had non-missing data. There are no significant differences between this subsample and the full SIPP analysis sample.

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