A Detailed Picture of Intergenerational Transmission of Human Capital[1]

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Executive Summary

Numerous studies have shown that composite or summary measures of intergenerational mobility, such as the intergenerational elasticity, can mask important differences in life chances for children whose parents fall along various points of the status distribution. For example, the same intergenerational elasticity can characterize both a society with high levels of mobility in the middle of the parental distribution and less mobility in the tails, as well as a society with moderate levels of mobility throughout the distribution.

Using data from the Health and Retirement Study (HRS), we consider how parental education relates to four separate outcomes in the children's generation: education, lifetime earnings, health and (financial) wealth. We relate parents' educational ranks to children's ranks on these four outcomes. By focusing on ranks, we are able to see full distributions of outcomes and can pick up within-group differences that even a relatively disaggregated analysis, like a quintile-based transition matrix, can obscure. We particularly focus on the tails of the children's distribution—the 10th and 90th percentiles—plus the median.

The "children" in this study are Americans who have recently retired or are approaching retirement age. We are thus observing them at a point when their outcomes reflect accumulated life experience. Although this age range is superior in several respects to point-in-time observations earlier in life, it does limit our ability to make inferences about future cohorts. It also raises some selection issues.

We find a mixed story. For a wide swath of the middle of the parental education distribution, the distribution of children's outcomes is extremely broad: for a given level of parental education, the most successful children (that is, those at the 90th percentile) end up at the top of the overall education, wealth, health and earnings distributions, and the least successful children (that is, those at the 10th percentile) for that same level of parental education end up at the bottom. This suggests a fluid and mobile society since children in the middle do not just end up in the middle: they end up at all points in the distribution in nearly equal measures. At both tails of the parental distribution, however, we see far closer correspondence between parents' and children's outcomes. The most successful children of parents with low educational ranking (that is, the 90th percentile of the children whose parents have the least education) have only average wealth, health or education; they attain about the median outcome. This pattern seems to be more pronounced for education, health and wealth than for lifetime earnings, which is arguably a poorer measure because of data limitations, most notably top-coding in the administrative earnings history data. The top-coding is quite pronounced for part of the period.

To provide a preliminary look at educational outcomes for three generations, we include the eldest children of the near-retiree HRS children in the first analysis. We find that persistence in the tails across three generations is higher than we would expect if we assumed that transition probabilities stayed the same across both generations. This suggests the need to us caution when making inferences about how many generations it takes to overcome the effects of parental privilege or disadvantage based on measures estimated using data from just two generations.

INTRODUCTION

Americans care deeply about levels of intergenerational mobility—the degree to which parents transmit their social and economic status to their children. Our nation espouses an American Dream, "that dream of a land in which life should be better and richer and fuller for every man, with opportunity for each according to his ability or achievement" (Adams 1931)[2]. This strong commitment to an ideal that anyone should be able to get ahead leads us to celebrate cases of upward mobility. Yet, at the same time, American's feelings about mobility are often quite complicated. As much as we may love stories of upward mobility and promote the need for level playing fields, few want to see their own children lose ground, so we often loathe downward mobility, even if it is a necessary side effect of upward mobility.[3]

Researchers have considered many different aspects of intergenerational mobility, given that there are so many forms of status, such as lifetime earnings, occupation, education, wealth and even health. No matter what specific indicators they examine, mobility researchers are typically trying to get at the broader concept of *human capital*. In its most general form, *human capital* encompasses potential lifetime earnings, based on health, social connections, education and various other factors. Because human capital is so difficult to measure, researchers often use years of education as a proxy. We follow this tradition and focus on connections between parents' and children's education. We supplement these analyses with an examination of connections between parent's education and other outcomes in the child's generation, including health, wealth and lifetime earnings.

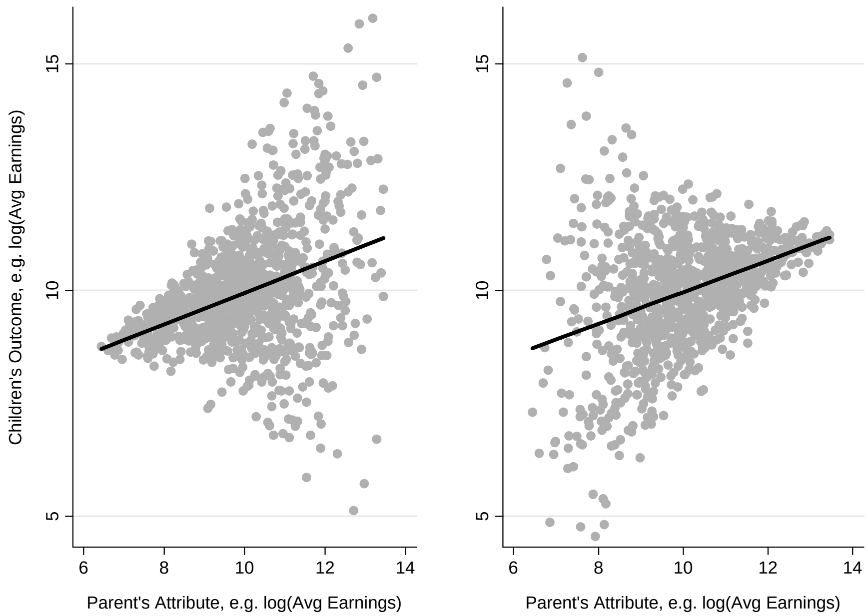
We argue that mobility has a different interpretation at the top and the bottom of these distributions. We focus on how the distribution of child outcomes varies across the distribution of parental characteristics. The data that we use allow us to see changes in mobility at the bottom of the distribution over several decades. Using a long time horizon has some advantages, especially in the case of financial wealth, as it is better measured relatively late in life. The "children" that we examine in our analyses are adults approaching retirement age in the past decade.

Throughout the paper we discuss only relative mobility. Over time, and across generations, outcomes improve on average, meaning that absolute mobility across generations is upward.[4] However, a child from a lower-ranked family can do better than his parents and still have a lower rank in his society than his parents had in theirs. The concept of relative mobility measures how well a child does relative to others of comparable age. For many policies, and for gauging the extent to which the American Dream is alive and well or whether playing fields are indeed level, relative mobility is more important.

Intergenerational Correlations or Regressions

Typically, intergenerational mobility is viewed through the lens of correlation or regression coefficients, called *the elasticity* when measured in percentage changes, between child and parent outcomes, but this masks the different variability of outcomes. With very different kinds of mobility opportunities, the same intergenerational elasticity or correlation could result.[5] Figure 1 shows a pair of hypothetical, randomly generated cases with markedly different kinds of mobility but the same intergenerational elasticity (IGE) coefficient[6] of 0.35, implying much regression to the mean. The figures could describe any relevant mobility measure, such as earnings, wealth or education, but, for convenience, we describe the graphs as earnings outcomes. In the figure to the left, we see that the children of low-earning parents are almost certain to have low earnings themselves, while children with higher-earning parents have higher average earnings and are more likely to diverge from their parents' level. In the figure to the right, in contrast, a very different pattern is apparent. The children of low-earning parents end up all over the distribution, and the children of the highest-earning parents are almost certain to be high earners, though they may not be the highest earners in their cohort. In both of these societies, the median or mean outcome for children across the distribution of family backgrounds does not capture the variability of outcomes.

Figure 1. Hypothetical IGE=0.35 Scenarios with Different Mobility Implications

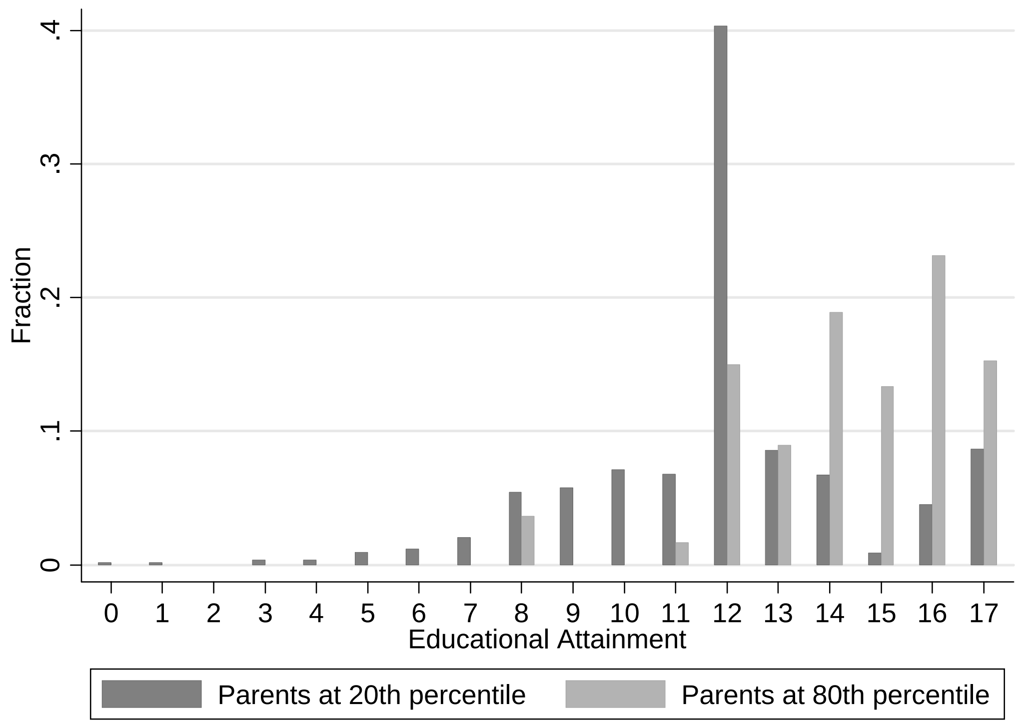


Note: "log" refers to the natural logarithm; an intergenerational earnings elasticity is the slope of a straight line on a graph of log earnings versus log earnings.

Comparing Distributions of Outcomes

As the example in Figure 1 illustrates, comparing the whole distribution of possible outcomes of children with parents who have different ranks could have distinct advantages over a single summary measure like the IGE. Figure 2, based on real data on Americans approaching retirement age, shows, for example, that the actual distributions of children's outcomes do differ based on parental status, with outcomes for adult children of higher-ranked parents shifted to the right relative to outcomes for children of lower-ranked parents. The 10th percentile of children of lower-ranking parents -- that is, the least scholastically successful children of the least educated parents -- have 9 years of education, while the 10th percentile of children of higher-ranking parents -- that is, the least scholastically successful children of the most educated parents -- have 12 years of education. The 90th percentile of children of lower-ranking parents is 16 years of education, while the 90th percentile of children of higher-ranking parents is 17 years of education, the maximum level of education reported on the survey. The median outcome for children of lower-ranking parents is 12 years, while the median outcome for children of higher-ranking parents is 14 years of education. The means are similar to the medians at 12.2 and 13.7, respectively.

Figure 2. Distribution of Children's Educational Outcomes for Lower and Higher Levels of Parental Education

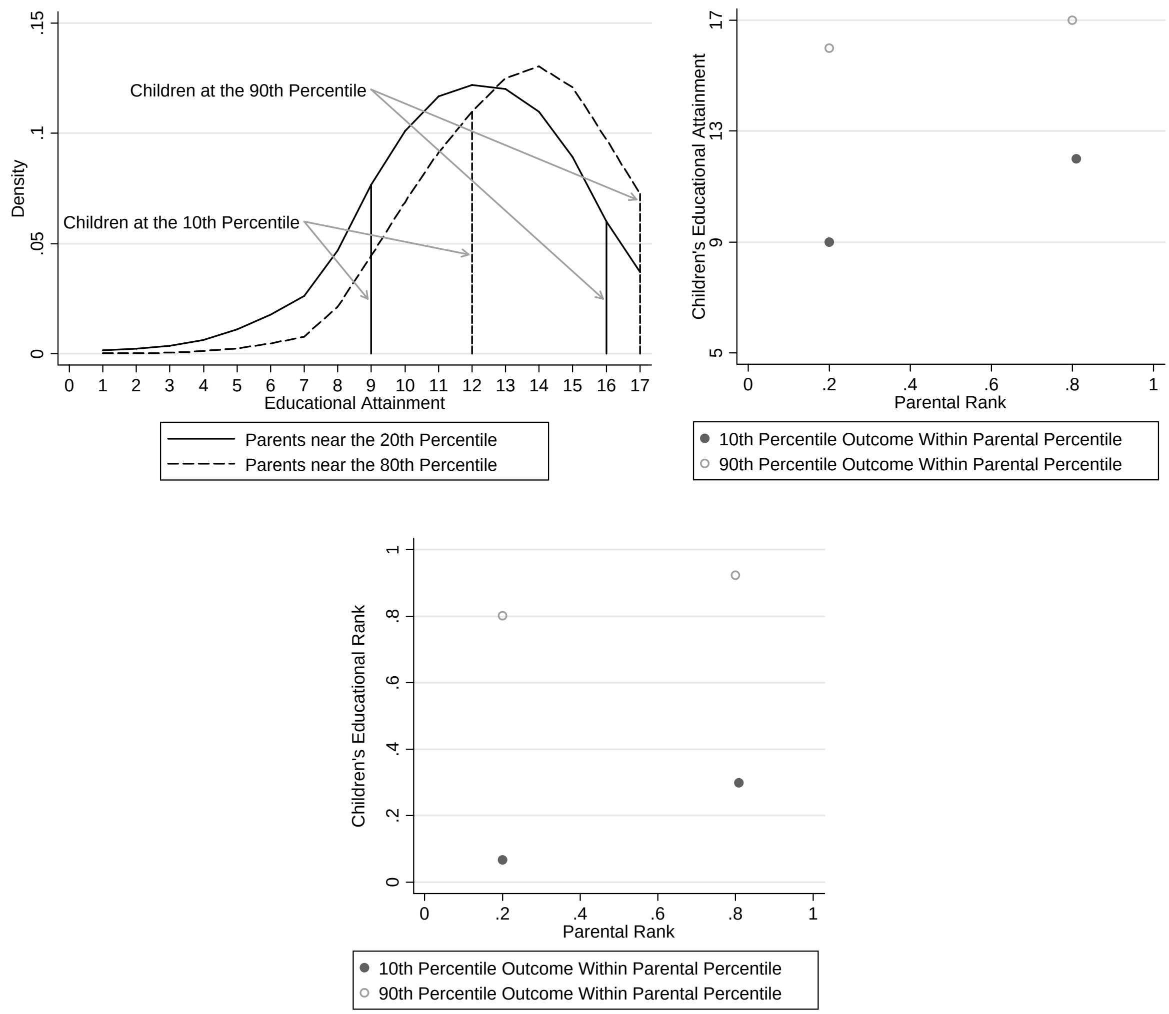


Source: Authors' tabulations from the Health and Retirement Study (HRS). Parents near the 20th percentile (ranks estimated at 0.15 to 0.25) have different education levels for different birth cohorts of HRS respondents, from 6.5 to 9 years attainment with the bulk of observations at 7 years, and parents near the 80th percentile(ranks estimated at 0.75 to 0.85) range from 12 to 13.5 years with the bulk at 12 years.

Picturing Mobility

Ideally, we want to compare these distributions of outcomes across all possible ranks of parents, not just those at the 20th and 80th percentiles, as displayed in Figure 2. This would require generating and interpreting a prohibitively large number of graphs and statistics or developing a method of summarizing all of these details. The method we use is to construct plots that show the 10th, 50th and 90th percentiles of child outcomes for every parental background type. We can then show summary measures of the distribution of child outcomes for every parent type on a single graph, connecting these points with lines. Figure 3 illustrates this approach, using, for simplicity, a continuous, or, smoothed, version of the histogram from Figure 2.

Figure 3. Translating Many Distributions of Outcomes into a Simpler Graph



The top left graph in Figure 3 contains four vertical lines, corresponding to the 10th and 90th percentiles of child's outcomes for parents at the 20th percentile of parental education (solid lines) and the 10th and 90th percentiles of child's outcomes for parents at the 80th percentile of parental education (dotted lines). We then translate these points to the graph on the right, where points on the distribution of child's outcomes are graphed versus parental rank. To understand how the top left graph maps to the graph at the top right, imagine that the bell-shaped curves on the left are turned on their sides so that the lines for the 10th and 90th percentiles now directly correspond to the lower and upper dots, respectively. The greater distance between the dots at the 20th percentile of parental education directly matches up with the wider curve for the less educated parents in the panel on the left side, and the smaller distance to the more condensed curve for the more highly educated parents.

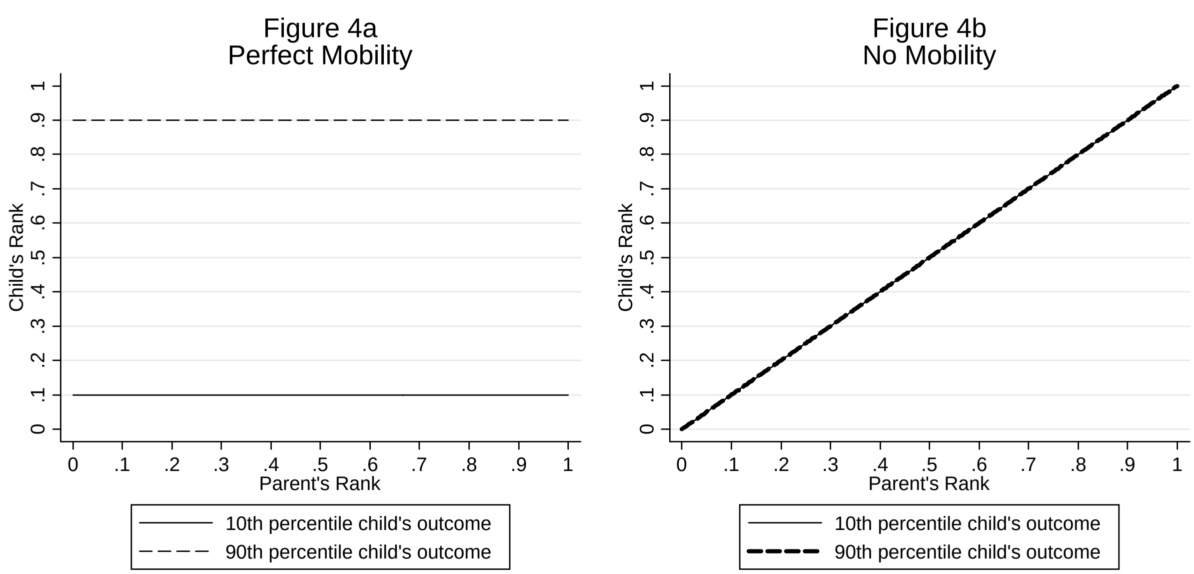
We can then fill in the rest of the points using every other parental rank in the data and connect the points to show the 10th and 90th percentile outcome of children as functions of parental rank. We also convert children's outcomes into their *rank* within the overall distribution of children of comparable age, rather than the absolute number of years of education, as shown in the bottom graph in Figure 3. Ranks for both children and parents are relative to the children's peers (those in the same five-year birth cohort), and ranks are computed using survey weights, so they reflect an estimate of the proportion of the surviving population of a comparable age who have that level of education or less.

Adjusting for birth cohort is necessary when speaking of relative mobility, since we are examining multiple cohorts, and the rank of someone with only a high-school education changes dramatically over cohorts as the population becomes more educated. This also ensures that outcomes are measured on a constant scale from zero to one (in rank) or equivalently, zero to 100 (in percentiles), for a variety of outcomes typically measured in very different units, including education, earnings, wealth and health. Thus, our detailed pictures are always drawn on a square with sides of length one (ranging from zero at the lowest point in the distribution to one at the highest point in the distribution), though it will be convenient to "stretch" the dimensions of the square to show detail at times (see Figures 6 to 9).

Interpreting These Detailed Pictures

Suppose a parent's percentile rank in society does not help predict a child's rank at all; then the expected 10th and 90th percentiles of a child's rank, conditional on parent's rank, would be the same regardless of parent's rank, running at 10 and 90 percent (the 10th percentile is a solid line, the 90th a dashed line) across the board (Figure 4a). This corresponds to a world of "perfect mobility." Sawhill and Morton (2007) call this the "fortune cookie" world to indicate that one's final rank in society is unrelated to parental background.

Figure 4. Hypothetical Scenarios with Perfect Mobility and No Mobility

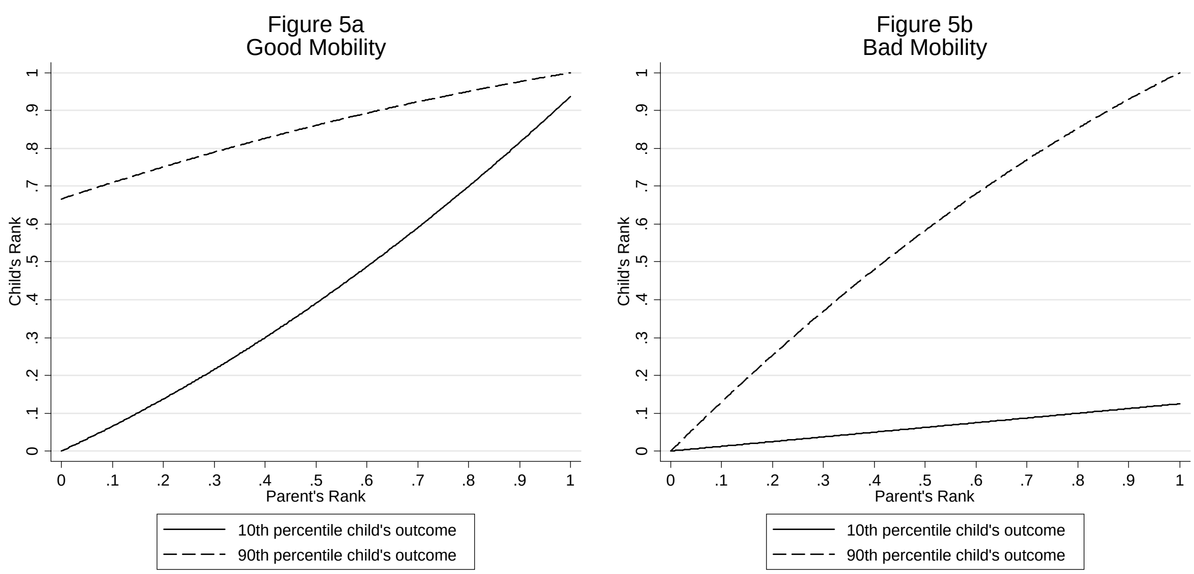


By contrast, if mobility were impossible, the tenth and ninetieth percentiles of a child's rank would be fixed at parent's rank, running on top of each other along the diagonal (Figure 4b, labeled "No Mobility"). Sawhill and Morton (2007) call this scenario the "class-stratified society," since one's final rank in society is perfectly predictable from parental background.

Figure 4b clearly depicts an undesirable lack of mobility, but the first "perfect mobility" world in Figure 4a also seems undesirable, since parents' investments in their children can have no impact on how they do unless such investments are independent of parents' rank. In the "perfect mobility" world, all status is randomly assigned and cannot respond to hard work, ingenuity or other forms of exercised ability.

Of course, neither extreme is observed in the real world, but two plausible hypothetical extremes are worth discussing. Imagine that the median outcome for the children at each parental rank is the parent's own parental rank (that is, the median child experiences "no mobility" as in Figure 4b), and consider the following two scenarios. In the first, illustrated in Figure 5a, the rank for a child (in society later as an adult) from the upper ranks is almost certainly close to his parent's rank. However, the rank for a child from the lower ranks is essentially unpredictable given only his parent's rank and may be driven by variation in ability or diligence or by pure luck. In the second scenario, illustrated in Figure 5b, the rank for a child from the lower ranks is almost certainly close to his parents' ranks, while the rank for a child from the upper ranks is essentially unpredictable given only his parent's rank.

Figure 5. Hypothetical Scenarios with "Good" and "Bad" Mobility



We might refer to these as "good" and "bad" mobility, respectively, reflecting the normative judgment that falling a percentile or two when one is in an upper-percentile family is unlikely to have severely negative consequences but could in lower-ranked families. Conversely, rising a percentile or two when one is in an upper-percentile family is unlikely to have large positive consequences but would in lower-ranked families. Moreover, lower-ranked families are very likely to prefer a world in which their children's future ranks are not predictable from their own, regardless of how the ranks of children of other parents are determined. On the other hand, higher-ranked families are very likely to prefer a world in which their children's future ranks are predictable from their own, regardless of how the ranks of other parents' children are determined. All of these considerations are satisfied in Figure 5a, but not Figure 5b.

Note that if the data fall into one of these two broad categories, very similar estimates of IGE can be obtained, as demonstrated in Figure 1. We are interested, however, not in the mean but in the distribution of quantiles and the way in which the quantiles change with a change in parental rank.[7]

If society cares about ensuring every child has a chance of upward mobility, as the perspective Rawls (1971) advances would imply, the likelihood that a child from the bottom of the socioeconomic spectrum stays there is the most important fact measuring equality of opportunity in our society. The same IGE could mask vastly different mobility at the bottom (or the top) of the distribution. As an alternative, we henceforth characterize the distribution of outcomes for children with various parental backgrounds using at least three quantiles: the 90th, 50th, and 10th percentiles.

PREVIOUS WORK

We show several previous estimates of the partial correlation of educational attainment across generations in Table 1 (see Hertz et al. 2007 for estimates of linear relationships and correlations between parent and child education levels for a large number of countries over a 50-year period). These estimates indicate that an extra year of parental education, *ceteris paribus*, is associated with roughly a quarter of a year more education for that parent's children.[8] However, most analyses are unable to distinguish between the effects of parental education itself and selection, the notion that those who seek out more education would likely encourage their children to pursue more education even absent their own opportunity to get more education.

Several authors of these analyses do use techniques designed to estimate the causal impact of education. In most cases, causal impacts are estimated to be lower than observational associations.[9] Estimates geared at identifying a causal effect address a policy concern, namely that average associations may not be similar to the marginal causal effect. This indicates that extending schooling to the less affluent may not be as effective at producing equality of opportunity as some cheaper alternatives. That is, granting additional education to those who are less educated in any cohort would likely have a smaller impact on the next generation's education than the observed differences between the children of those with more and less education (see Jencks and Tach 2006 for similar observations on mobility investments more broadly). The opposite relation is also possible.

This policy concern may not be as relevant if one is focused on the current extent of equality of opportunity or intergenerational mobility rather than the relative effectiveness of exogenously imposing additional schooling in improving mobility. Because we are focused on measuring mobility at different starting points in the distribution (and, secondarily, seeing if this pattern changes across birth cohorts), we ignore these problems of causal interpretation.

No previous work estimates the distributions of outcomes at a large number of values for parental educational attainment, which is necessary to construct the graphs shown above (e.g., in Figure 2). Such estimates are hard to find for income mobility as well, though see Dahl and DeLeire (2007) and Bratberg, Nilsen, and Vaage (2007). In addition, it is difficult to construct estimates of changes in educational intergenerational mobility over time from previous work. Estimates of changes in economic intergenerational mobility were also hard to find until the past few years: see Aaronson and Mazumder 2005, Mayer and Lopoo 2005, Lee and Solon 2006, Hertz 2007, Bratberg, Nilsen, and Vaage 2007, Pekkala and Lucas 2007 and Mazumder 2007 for recent innovations.

Table 1. Estimates of Intergenerational Persistence in Education

Citation	Coeff	Relationship examined	Years	Notes
Blau and Duncan (1967)	0.310	F-son, US	1962	pp. 170, 174
Bowles (1972)	0.204	F-son, US	1962	
Hauser and Featherman (1976)	0.251/ 0.254	F-son, US	1962/1973	As low as 0.206
Olneck (1977)	0.45	F-son, MI	1973/73	Odd sample
Behrman and Taubman (1985)	0.31	F-child, US	1980/80	
Case and Katz (1991)	0.095	P-child, Boston	1989	Inner city
Lillard and Willis (1994)	0.19 0.23	F-son, Malaysia F-daughter, Malaysia	1988/88	
Couch and Dunn (1995)	0.27 0.20	F-son, US F-son, Germany	1984/84	
Mulligan (1997)	0.32 0.33	F-son, US F-child, US	1968/84-9	
Behrman and Rosenzweig (2002)	0.133 0.251 0.242 0.327	M-daughter, Minnesota F-daughter, Minnesota M-son, Minnesota F-son, Minnesota	1993	Twins M-child estimates near zero
Chevalier (2004)	0.1	P-child, UK	1994-2002	IV twice as large
Plug (2004)	0.276 0.268	M-child, Wisconsin F-child, Wisconsin	1957/1992	Smaller estimate for adopted children
Sacerdote (2002)	0.299 0.069 0.401 0.277	P-child, Holt biological P-child, Holt adopted P-child, NLSY biological P-child, NLSY adopted	1970-1980 / 2003 1979/2003	Holt adoptees Korean-Americans *randomly* assigned to families.
Black, Devereux, and Salvanes (2005a)	0.237 0.212 0.264 0.217 0.209 0.226	M-child, Sweden M-son, Sweden M-daughter, Sweden F-child, Sweden F-son, Sweden F-daughter, Sweden	1970/2000	IV estimates near zero except for M-son.

Notes: Mulligan (1997, Table 7.4, p.200) provides five rows of this table. 'M' indicates mother, 'F' indicates father, 'P' indicates parent, IV=instrumental variables.

Relatively few studies have used our data source, the Health and Retirement Study (HRS), described further below, to consider intergenerational mobility in the United States. Mobility researchers have used the Panel Study of Income Dynamics (PSID) and National Longitudinal Studies (NLS) far more extensively. Several of those studies that do use the HRS have focused on the intergenerational effects of various status measures on health outcomes (see, for example, Luo and Waite 2005 and Hamil-Luker and O'Rand 2007).

DATA AND METHODS

We estimate a "reduced form" model, given that our aim is primarily descriptive. Even a simple model of the mechanisms by which parental human capital (as reflected by characteristics such as financial resources, work and time at home, health and educational attainment) affect children's outcomes, such as schooling, health, labor force attachment and net worth, is extremely complicated.[10] The evidence discussed along with Table 1 suggests that our reduced form estimates likely represent an upper bound on the true causal impact of parental characteristics.[11]

Specifically, we compute quantiles of respondents' outcomes by parental characteristics using respondents' sample weights. We compute percentiles of education (and later, health, wealth, and lifetime earnings) by five-year birth cohort and call this *rank*. We then compute percentiles of rank by birth cohort and parental education and graph these against parental education. This tells us where in the cohort-specific distribution a child with a given parental education background will tend to wind up. We also smooth these estimates using locally weighted quantile regression.[12]

To a limited degree, we incorporate the next generation's outcomes in the last section, using the reported educational attainment of our sample members' oldest child.

To estimate the effects of parental status on children's and grandchildren's outcomes in these ways, we use data from the HRS matched to restricted-use Social Security Administration earnings records (the Summary Earnings Record, or SER). The HRS is a nationally representative, longitudinal survey of Americans over age 50, with oversamples of African-Americans, Latinos and Florida residents. The original sample reflects persons in households (the non-institutional population), though these sample members are subsequently followed if they move into institutions. HRS follow-up interviews occur every two years. These analyses include data from 1992 through 2004 for members of the original HRS cohorts (born in 1931 through 1941), from 1998 through 2006 for members of the war babies cohorts (born in 1942 through 1947), who were added to the HRS sample in 1998, and from 2004 though 2006 for members of the early baby boomer cohorts (born in 1948 through 1953). We also include any spouses of members of these cohorts in our sample if they meet the age criteria for the analyses. We focus on the 1935 and later birth cohorts because we have more complete earnings history data for them.[13]

Table 2 shows the characteristics of the HRS sample and illustrates how the sample size changes with the various restrictions we impose on the analyses because of data limitations and analytic choices. As the table indicates, these data have several important limitations related to their selectivity. We minimize these limits by using as few restrictions as possible when choosing the sample for each analysis; that is, we do not require individuals to have an earnings record in the analyses of education, health or wealth.

Perhaps the most important element of selection appears in the lifetime earnings analyses and is due to incomplete match rates to the earnings records (see Table 2, row 5 compared to row 3). HRS respondents were asked both in the baseline interviews and again in 2004 whether they would grant permission to link their survey responses to earnings records, including data on Social Security-covered earnings from 1951 onward and total earnings from 1981 onward. After these two requests, the rate for matches to the administrative earnings records is about 80 percent for members of the original HRS cohorts, closer to 70 percent for the war babies and just under half for the early baby boomers. Validation analyses suggest that those individuals in the HRS cohorts without matches to the administrative data differ systematically from those with matches (Haider and Solon 2000, Kapteyn et al. 2006). For example, self-reported non-workers are less likely to offer their Social Security numbers than those with work experience, non-whites are less likely to offer the matching information than whites and matches are associated with other measures of status like reported wealth.

Table 2. Characteristics of the Health and Retirement Study Sample: Individuals ages 51–62 in 1992–2006 in Various Analyses

		Number	Percent
1	Full sample	7,702	n/a
2	Just 1935+ cohorts	7,301	100.0
3	Includes education data for at least one parent	6,746	92.4
4	Row 3, plus non-missing education data	6,744	92.4
5	Row 3, plus summary earnings record (SER) match	4,077	55.8
6	Row 3, plus non-missing wealth data	6,746	92.4
7	Row 3, plus non-missing health, disability data	6,735	92.2

Notes: Sample uses the latest person-year observation through age 62 for each sample member. Only respondents and spouses with non-zero weights are included in the analyses. We use wealth imputations where available.

Social Security-covered earnings data are further limited in that they only include earnings that the program covers up through its wage and benefit base, also known as the taxable maximum, set at $102,000 in 2008.[14] They are thus missing the earnings of the highest earners and those workers in jobs not covered by Social Security. The fraction of earners whose earnings are capped in the SER has varied historically, reaching a high point of 36.1 percent of covered workers—and nearly half (49.0 percent) of men with covered earnings—in 1965 (Social Security Administration 2008, Table 4.B4). In 2005, about 6.1 percent of covered workers had earnings over the cap.

Another data limitation is the fact that about 1 in every 13 HRS respondents (7.6 percent) was not able to report an educational level for either parent (see Table 2, row 3 compared to row 2). Tabulations reveal that HRS respondents who do not report parental education are significantly less educated than those who did, with an average of about two and a half fewer years of schooling than those reporting education for at least one parent. Such respondents also have lower lifetime earnings and wealth, and they report worse health.

Data are also missing due to mortality, which may induce selection (a larger problem for men than for women, given men's higher mortality in prime age).[15] The specific concern is that those individuals who do not survive into their early fifties, the age of the first HRS interview, may differ significantly in profile from those who do. Evidence on differential mortality suggests that mortality is higher for those with lower socioeconomic status and that the gap between lower- and higher-status groups may be growing (see, for example, Singh and Siahpush 2006 and Meara et al. 2008). To minimize the effect of this selection and maximize the generalizability of findings, we use data for individuals up to their 62nd birthday and exclude later data.[16] Thus, our findings are representative of U.S. non-institutionalized persons aged 51 to 62 in 1992 through 2006. One advantage of using data on these cohorts (rather than on younger Americans) despite these selection problems is that certain outcomes, like wealth and lifetime earnings, are better reflected later in life given the different earnings and wealth trajectories of individuals who complete school and enter the labor force at different ages.

Parental Education

Our main explanatory variable is the educational attainment of an HRS sample member's parents. This is as reported by the adult child in the baseline interview and so is subject to a number of potential biases (e.g., it is retrospective rather than contemporaneous, children could misreport if there is stigma/prestige associated with parental education of various levels or children simply may not know how much school either or both of their parents completed).

We use the average attainment of both parents except for those respondents who report education for just one parent. For the vast majority of sample members who report educational attainment for both parents, the distributions of mother's and father's education are quite similar and thus exhibit strong evidence of positive assortative mating, the tendency of individuals to select partners of similar status and background (i.e., the educational attainment of mothers and fathers is highly correlated).[17] Across the HRS cohorts, parental education increases markedly, from a median of 9 years for the parents of HRS respondents born in the late 1930s to a median of 11 years for the parents of HRS respondents born in the early 1950s.

Outcome Measures for HRS "Children"

Education: We use completed years of education to reflect the adult child's educational preparation. HRS respondents have roughly similar distributions of education across birth cohorts, but there is a secular increase in educational attainment, as in the parents' generation, though less dramatic for these later cohorts (Appendix Figure 1). The proportion with exactly 12 years of education falls in every cohort, and the proportion with 16 or more years increases.

Earnings: Our measure of the child's lifetime earnings is average indexed monthly earnings (AIME) over the top 35 earnings years before the respondent turns 62 (i.e., using Social Security rules to calculate AIME as of the 62nd birthday). This measure reflects Social Security–covered earnings, so only earnings below the program's taxable maximum, currently (in 2009) set at $106,800 annually, and in jobs covered by the program, thus excluding a small fraction of earners, mostly employees of state and local governments. All dollars are normalized to 1992 dollars. As Appendix Figure 2 shows, the AIME distribution is skewed, with a low mode (a peak below $500 a month) and long upper tail.

Health: Our measure of a child's health status combines self-reported health status, disability status and duration and presence of limitations in activities of daily living (ADLs) in a linear way to create a 32-category health scale.[18] Specifically, we start with a five-category health status code (where 1 is excellent and 5 is poor) and then add one-half times an indicator for the lowest health status (turning a 5 on the 5-point scale into a 5.5) given that poor health appears to have a non-linear effect of on key outcomes (i.e., the distance between poor health and fair health is far relative to the distance between any other pairs of health status categories). We then add one-half times an indicator for any ADLs, add one- half times an indicator for Social Security disability program duration of less than or equal to 2 years, add one-quarter times an indicator for any disability duration 3 to 10 years, and add one-tenth times an indicator for disability duration greater than 10 years (loosely reflecting patterns identified by Zayatz 2005).[19] This sum ranges from 1 to 6.5 so we subtract 1, divide by 5.5 and subtract the result from 1. The scale runs from zero (very unhealthy) to one (healthiest). This transformation mainly introduces extra variation in the worse health reports ("fair" or "poor"), as shown in Appendix Figure 3, and predicts observed mortality well.[20]

Assets: We define net worth as the sum of the child's financial assets (checking and savings accounts, certificates of deposit, stocks, bonds, mutual funds, Individual Retirement Accounts and Keogh accounts, money markets), homes, other properties and business assets less debt, including mortgages, all converted into real (year 2000) dollars. This measure does not include Social Security wealth or wealth in employer-sponsored pensions, both important components of retirement security. The distribution of net worth changes to become more bimodal across the HRS birth cohorts. As Appendix Figure 4 shows, the mode shifts slightly to the right but the proportion with $1 or less in net worth first decreases then rises sharply.

RESULTS

Since the meaning of parental education may change over time, we turn years of education into a percentile rank in order to analyze the relationship between parental rank and children's outcomes (i.e., parental rank is measured along the horizontal axis in Figures 6 though 9). Parental education is converted into rank of parental education within birth cohort of children, and smoothed relationships between ranks are computed using locally weighted quantile regression.

Looking first at education of respondents as a function of their parents' educational rank (Figure 6), mobility at the top and bottom of the distribution is relatively low. Half of children born to parents in the bottom decile (who survive long enough to be seen in the HRS in 1992) will be in the bottom third of their cohort's educational attainment, and 90 percent of them will be in the bottom three quartiles of their cohort's educational attainment.

The median educational outcome for children is steeply increasing in parental characteristics, implying that the central tendency of children's outcomes is strongly determined by parental status. However, the median educational outcome is much flatter in the middle range and increasing at a faster rate in the lower and higher ranges of parental education, implying that the effect of parental characteristics is nonlinear, with small improvements in status for those parents with low or high status generating larger returns than those with median status.

Translating these disaggregated results for the intergenerational persistence of education into a single summary measure (as the literature review in Table 1 displays), we see that the HRS data suggest a higher estimated intergenerational coefficient than some of the prior sources (Table 3). The results in the table suggest that the persistence estimates vary based on how one treats parental education, especially for individuals missing data on one parent. The estimates that include data on one parent when that is all that is available (e.g., the average or maximum parental education) are higher than the estimates on mothers' or, especially, fathers' education alone.

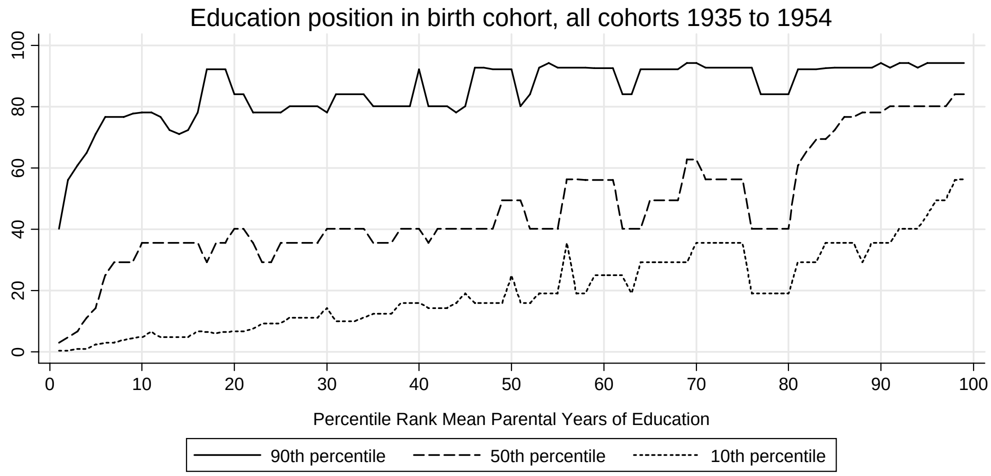
Table 3. Intergenerational Persistence of Completed Years of Education in the Health and Retirement Study Sample: Individuals Ages 51–62 in 1992–2006

	Daughters	**Sons**	**All children**	
	Coefficient	Coefficient	Coefficient	N
Father's education	0.32	0.32	0.32	6,006
Mother's education	0.37	0.36	0.37	6,558
Highest parent education	0.39	0.41	0.40	6,744
Average parent education	0.41	0.41	0.41	6,744

Notes: Sample uses the latest person-year observation through age 62 for each sample member born 1935 and later. Coefficients are from Ordinary Least Squares regressions which include controls for the child's birth cohort and use respondent weights. Only respondents and spouses with non-zero weights are included in the analyses.

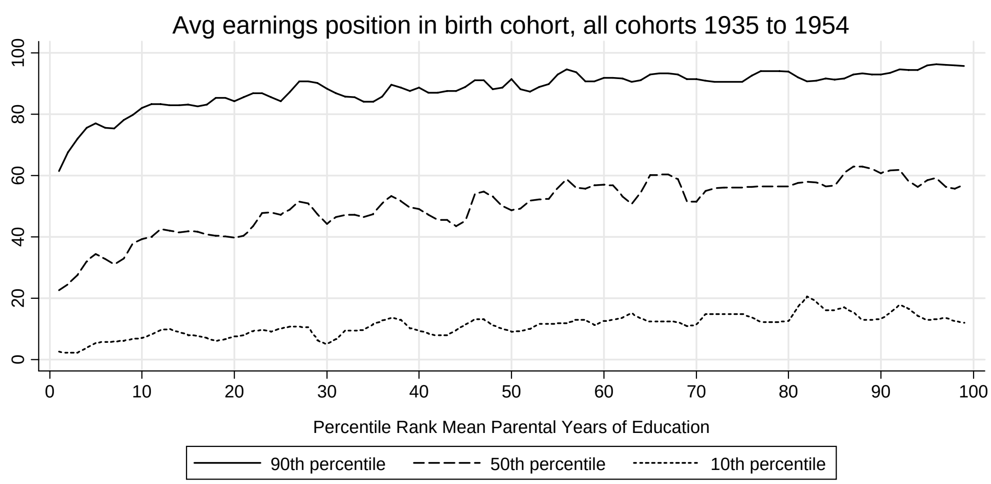
Returning to the disaggregated analyses on the other outcomes, similar patterns are clearly visible in health (Figure 9) and, to a lesser extent, wealth (Figure 8) and lifetime earnings (Figure 7). The less pronounced lifetime earnings pattern may be due in part to our measure, which is top-coded and confounds low or no earnings with earnings in employment not covered by Social Security. The median lifetime earnings rank increases from about the 20th percentile to roughly the 60th percentile as parental education increases, and the median wealth rank increases from about the 20th percentile to roughly the 80th percentile, so wealth is more strongly determined by family background than earnings. Wealth and earnings also have more of the flavor of "bad" mobility, where the distribution is tighter for low parental education levels and "fans out" as parental education increases. Education and health have more of a mix of "good" and "bad" mobility (see Figure 5), where the distribution of children's outcomes is tighter for both high and low levels of parental education and more disperse for intermediate values.

Figure 6. Distribution of Educational Percentile Rank by Parental Education Percentile



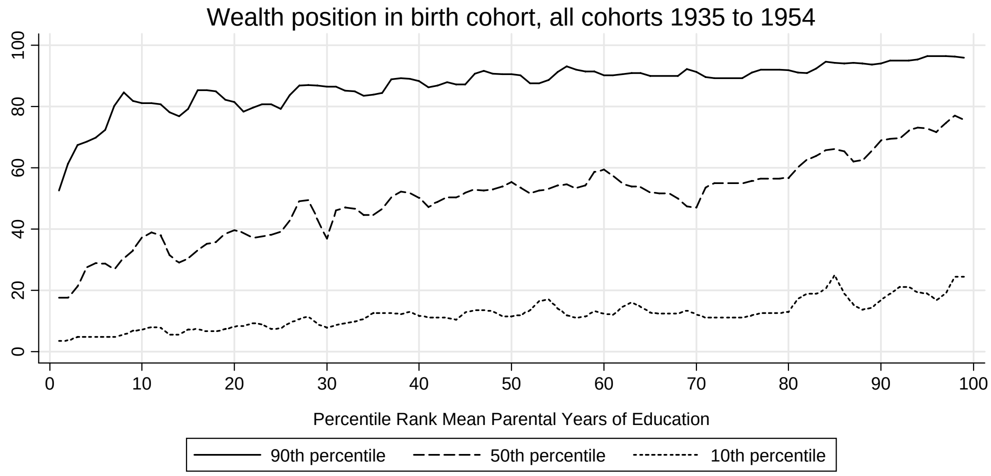
Source: Authors' tabulations from the Health and Retirement Study; estimates computed using local (kernel-weighted) quantile regressions of the within-cohort rank of outcome on the percentile rank of parent's education (average of mother and father) within cohort.

Figure 7. Distribution of Lifetime Earnings Percentile Rank by Parental Education Percentile



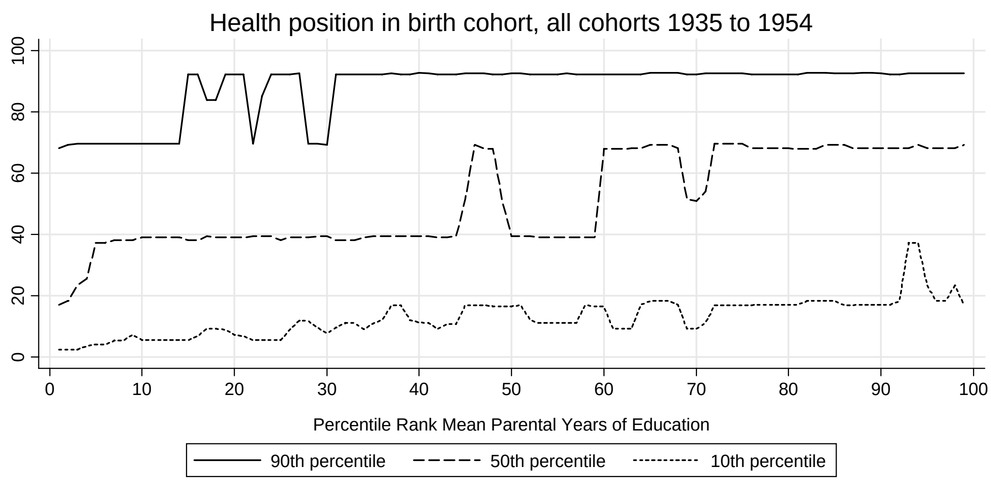
Source: Authors' tabulations from the Health and Retirement Study; estimates computed using local (kernel-weighted) quantile regressions of the within-cohort rank of outcome on the percentile rank of parent's education (average of mother and father) within cohort.

Figure 8. Distribution of Wealth Percentile Rank by Parental Education Percentile



Source: Authors' tabulations from the Health and Retirement Study; estimates computed using local (kernel-weighted) quantile regressions of the within-cohort rank of outcome on the percentile rank of parent's education (average of mother and father) within cohort.

Figure 9. Distribution of Health Percentile Rank by Parental Education Percentile



Source: Authors' tabulations from the Health and Retirement Study; estimates computed using local (kernel-weighted) quantile regressions of the within-cohort rank of outcome on the percentile rank of parent's education (average of mother and father) within cohort.

In every graph, the most noticeable deviation from perfect mobility is at the bottom of the distribution of parental rank, where children's outcomes are compressed, and a small increase in parental rank produces large improvements in the prospects of children. By the time parents are at the 20th or in some cases even the 10th percentile, their children's outcomes are largely similar to those of the broad bulk of the distribution.

Because of the strong visual impact of the individuals in the lowest few percentiles, it is useful to consider the characteristics of individuals with very low education in the HRS. We see that about three-quarters of the HRS respondents (the "children" in these analyses) who report zero education were born outside of the United States, as were about half of those who report less than three years of education (roughly the first decile). To try to better understand whether immigrant status might be driving these results, we restrict the sample in these graphs to parent-child pairs in which the child was born in the United States (Appendix Figures 5 through 8, which can be directly compared with Figures 6 though 9).[21] These analyses reveal broadly similar patterns to the graphs with the more inclusive sample. This suggests that the findings are not driven by the special experiences of immigrant children.

Third-generation Outcomes

The children of HRS respondents are of widely varying ages in the 1992 to 2006 survey years, but for the vast majority of respondents, we can construct some measure of their oldest child's outcome.[22] The most reliably comparable measure is educational attainment, which we compute for the oldest children only when that child is older than 24 and under 60 when we observe his or her outcome. We can then compute transition matrices across three generations, comparing the probability that an HRS respondent winds up with a given educational attainment conditional on his or her parent's education and the probability that the child of an HRS respondent winds up with a given educational attainment given the respondent's education.

The transition matrices (Tables 4 through 6) show an earlier generation's five-year-birth-cohort-specific quintile across the top, corresponding to columns of the matrix and a later generation's five-year-birth-cohort-specific quintile along the left side, corresponding to rows of the matrix. Every cell shows percentages, and the columns sum to 100, indicating that whatever quintile an antecedent appears in, his or her descendant must wind up in one of the five categories shown along the left side. Note that in every matrix, the sample weight is that of the HRS respondent, so parents' contributions and children's outcomes are representative of the middle generation.

Because we measure education imprecisely (specifically, as reported years of education), the different generations cannot be neatly broken into quintiles with exactly twenty percent of the population in each. There are some specific educational groupings that contain more than twenty percent of the population (see Appendix Figure 1, where each generation has a mode at 12 years of education), and we need to classify individuals with the exact same reported education as being in the same quintile. There are thus larger and smaller quintiles in each of the transition matrices (for example, quintile 2 is unusually small for the children in Table 3, but large for the children in Tables 5 and 6). Readers will thus want to compare estimates in any given cell of the matrix with the average indicated in the last column on the table, rather than with 20 percent.[23] So, for example, the first cell in Table 4 (for the transition from the bottom quintile to the bottom quintile) reflects the outcome for over 40 percent of the children in the bottom, compared to the 14.76 percent that we would expect if education were distributed randomly, as in the perfect mobility or "fortune cookie" world we describe earlier.

Table 4. Education Transition Matrix for Two Older Generations

		Parent's Education Quintile (Parent of HRS respondent)					
		Bottom	2nd	Middle	4th	Top	Total (avg)
Child's education quintile (HRS resp.)	Bottom	40.21	17.14	10.18	5.37	4.16	14.76
	2nd	4.39	3.17	4.50	2.49	1.37	3.04
	Middle	23.15	34.90	25.37	31.30	16.50	25.22
	4th	22.95	28.34	40.26	35.83	33.96	32.31
	Top	9.29	16.45	19.70	25.01	44.02	24.67
	Total	100.00	100.00	100.00	100.00	100.00	

Source: Authors' tabulations from the Health and Retirement Study

Table 5. Education Transition Matrix for Two Younger Generations

		Parent's Education Quintile (HRS respondent)					
		Bottom	2nd	Middle	4th	Top	Total (avg)
Child's education quintile (child of HRS resp.)	Bottom	17.70	11.11	3.67	2.49	1.38	5.02
	2nd	47.54	43.55	37.88	30.09	12.37	30.67
	Middle	17.24	22.52	25.01	25.90	19.07	22.61
	4th	1.33	1.34	1.43	2.70	2.39	2.06
	Top	16.20	21.48	32.01	38.82	64.79	39.64
	Total	100.00	100.00	100.00	100.00	100.00	

Source: Authors' tabulations from the Health and Retirement Study

Table 6. Education Transition Matrix for Oldest and Youngest Generations

		Grandparent's Education Quintile (parent of HRS respondent)					
		Bottom	2nd	Middle	4th	Top	Total (avg)
Grandchild's education quintile (child of HRS resp.)	Bottom	10.90	6.58	3.86	2.70	2.07	5.02
	2nd	40.47	34.62	32.55	30.04	20.30	30.67
	Middle	20.15	22.66	24.38	21.80	23.62	22.61
	4th	2.08	1.73	2.07	2.66	1.88	2.06
	Top	26.40	34.41	37.14	42.80	52.13	39.64
	Total	100.00	100.00	100.00	100.00	100.00	

Source: Authors' tabulations from the Health and Retirement Study

Often, transition matrices like these are used to determine the odds of a distant descendant reaching some higher status given that his antecedents started at the bottom, such as the distribution of great-grandchildren's life chances. A frequent assumption is that transition matrices describe a process where the transitions between two states at a point in time do not depend on the transitions made to get to a state or the point in time (i.e., a Markov process). In the real world, of course, history matters, and the transition probabilities change over time. We can strongly reject the assumption that history does not matter by looking at, for example, the probability of staying in the bottom or top quintile for two generations, a commonly used measure of mobility.

The parents of HRS respondents who found themselves in the bottom quintile of the education distribution—always less than an 8th grade education, fairly common in the days before the spread of high schools throughout the United States—had children with about a 40 percent chance of winding up in the bottom quintile (less than a high school degree or less than a 10th grade education, depending on birth cohort). HRS respondents who found themselves in the bottom quintile of the education distribution had children with about an 18 percent chance of winding up in the bottom quintile. If the outcomes for children depended on the prior generation alone, we could multiply these probabilities to find that grandchildren of parents of HRS respondents in the bottom quintile would have about a 7 percent chance of winding up in the bottom quintile, but the direct two-period transition matrix shows that probability is higher than expected, about 11 percent instead. This indicates mobility at the bottom is lower than the transition matrix seems to imply.

Similarly, the parents of HRS respondents who found themselves in the top quintile of the education distribution (some college) had children with about a 44 percent chance of winding up in the top quintile (college graduates). HRS respondents who found themselves in the top quintile of the education distribution had children with about a 65 percent chance of winding up in the top quintile (also college graduates). If the outcomes for children depended on the prior generation alone, we could multiply these probabilities to find that grandchildren of parents of HRS respondents in the bottom quintile would have about a 29 percent chance of winding up in the bottom quintile, but the direct two-period transition matrix shows that probability is higher than expected, about 52 percent instead. This indicates mobility at the top is much lower than the transition matrix seems to imply.

It is possible that some of this excess persistence is due not to true persistence but to errors in measuring true socio-economic status, so that the prior generation's measured status is informative about the parent's true status conditional on observing the parent's status. However, as difficult as it is to conclude with any confidence what proportion of observed excess persistence is due to true persistence and what proportion is due to measurement error, it is clear that transitions across one generation are not sufficient information for predicting multigenerational transitions rates.

CONCLUSIONS

Given parental education or the rank order of parental education within birth cohort, there is surprisingly high predictability of median educational outcomes. The same pattern is visible in other outcomes, especially wealth and health, but less so for lifetime earnings. The broad bulk of the distribution of outcomes is more concentrated among higher-status parents and more disperse among the lowest status parents, reflecting what we characterize as "good" mobility.

All cohorts seem to exhibit greater mobility near the bottom, especially when considering the 90th percentile of the second generation's within-cohort rank. However, median outcomes are clearly upward sloping in every graph, and, with the exception of educational attainment, the 10th percentile is moderately upward sloping in most graphs. This is weak evidence of "good mobility," where high-status parents are relatively confident of having high-status kids, but lower-status parents cannot predict their children's status.

Relaxing our search for a fanning out of percentiles moving from left to right ("bad mobility") or from right to left ("good mobility"), where high parents' status is on the right side of the graph, we can see a different empirical regularity. Many pictures show a pattern where low status of parents predicts low status of children and high status of parents predicts high status of children, but the broad middle cannot predict their children's status (consistent with Dahl and DeLeire 2007, and Bratberg, Nilsen, and Vaage 2007).

Comparing education across three generations using transition matrices, we find that there is more persistence than looking at any pair of generations would seem to indicate. That is, we strongly reject the Markov assumptions often made in connection with transition matrices.

Other estimates of intergenerational mobility in educational attainment indicate that the associations observed are likely an upper bound on true causal impacts; often, quasi-experimental "causal' estimates of the association between parent and child education are a quarter or less of the ordinary measure of association using observational data. However, there are no causal estimates of the spread of outcomes for children by parental rank, which is the main focus here. There are also no prior estimates on the suitability of assuming a Markovian process to project convergence to mean outcomes for descendants of someone above or below the middle group in a given generation, which we strongly reject for educational attainment.

If we think our estimates are upper bounds on the true causal impact of a parent's rank in society on children's outcomes, given how much selection is involved, then, if a parent could be moved up in social rank in terms of education or some other attribute via some exogenous policy, the effect on children would be smaller than many of the observational effects we measure. On the other hand, persistence across multiple generations is likely much higher than we can estimate given data limitations on multiple generations, and it is unclear whether we over- or under-estimate persistence at the top and bottom of the distribution.

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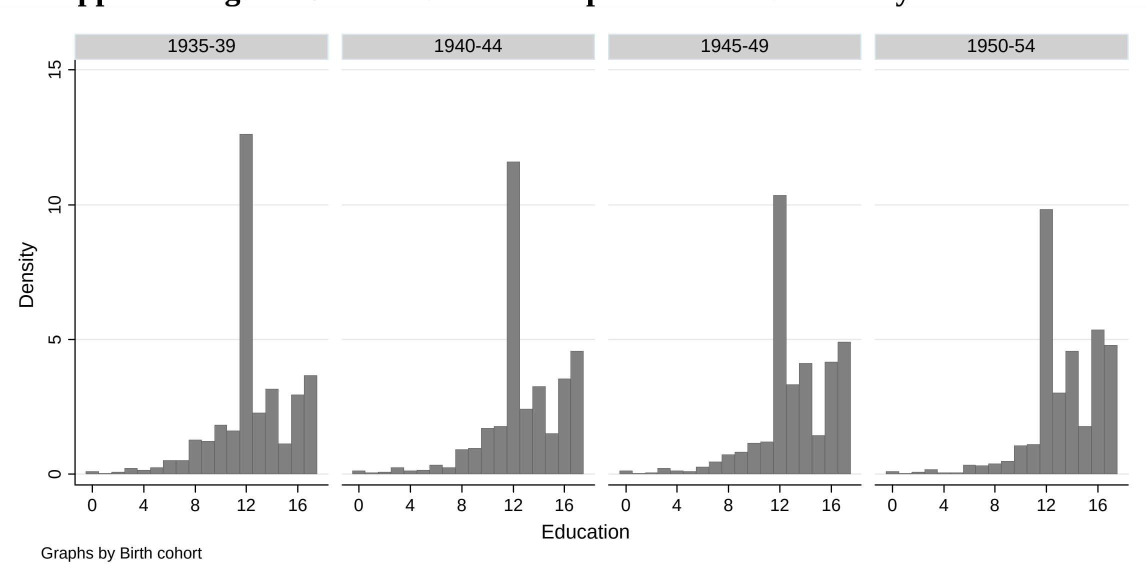
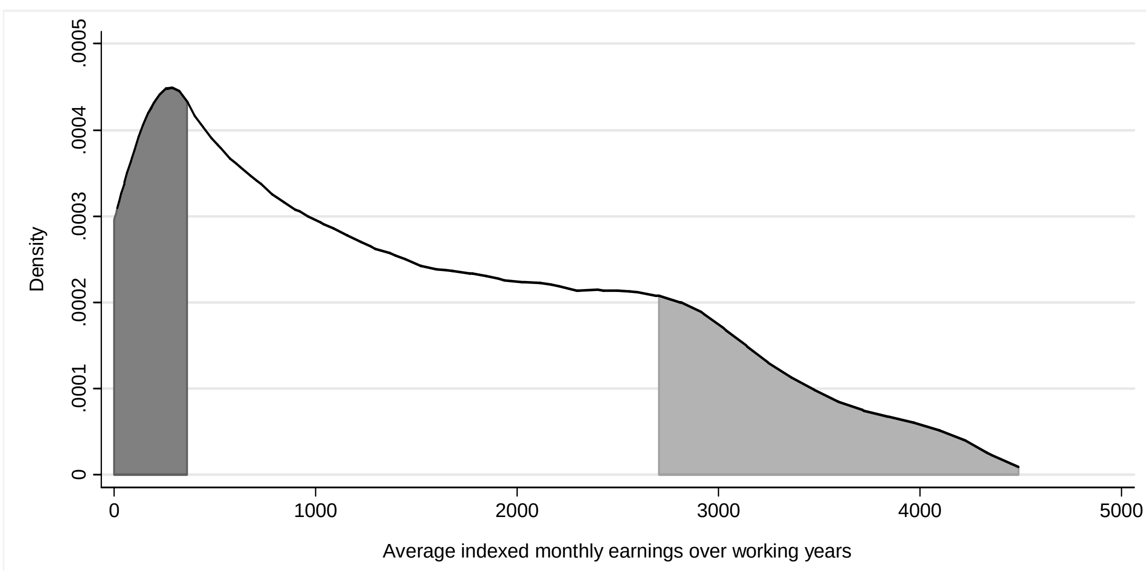
Appendix:
Distributions of Children's Characteristics

Appendix Figure 1. Distribution of Respondents' Education by Birth Cohort



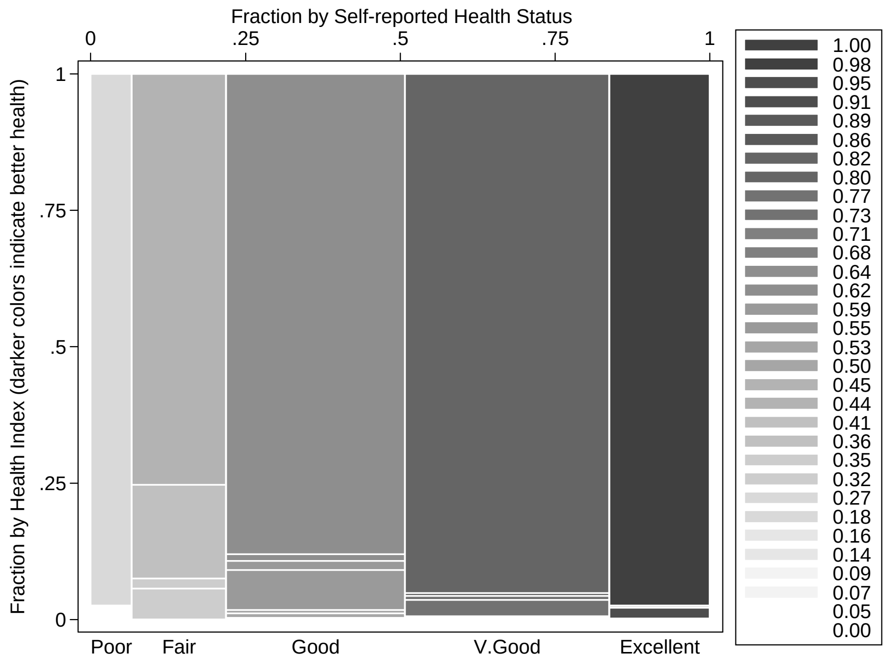
Source: Authors' tabulations from the Health and Retirement Study

Appendix Figure 2. Distribution of AIME ($1992) at Age 60/61
(bottom and top quintiles shaded)



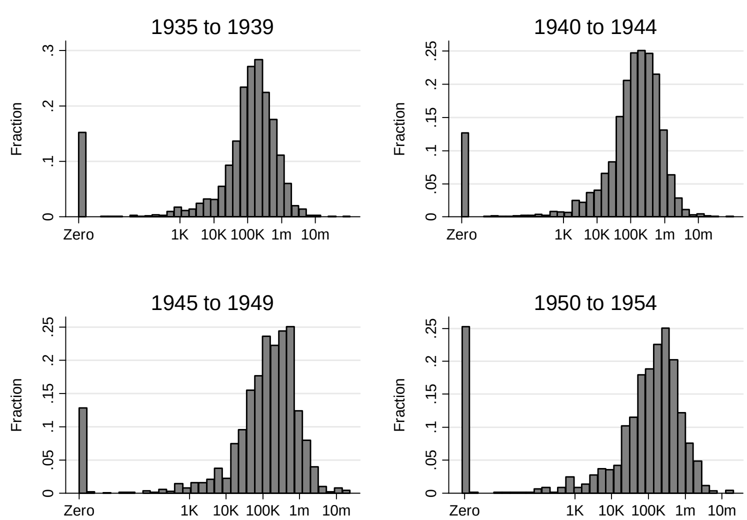
Source: Authors' tabulations from the Health and Retirement Study, matched to Summary Earnings Record (1951-2006), supplemented by self-reports

Appendix Figure 3. Distribution of Health Outcomes: Relationship between Self-reported Health Status and Health Index



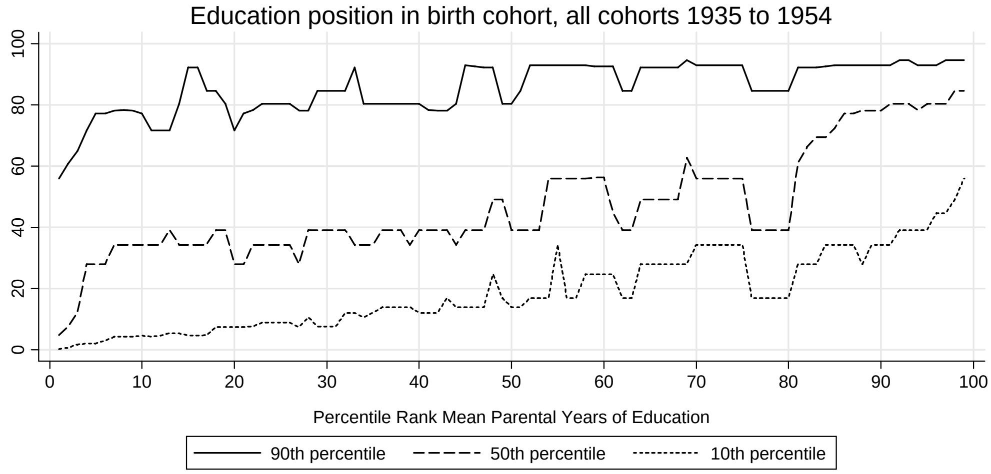
Source: Authors' tabulations from the Health and Retirement Study
Note: Shading reflects the value of the health index, as indicated by the legend

Appendix Figure 4. Distribution of the Natural Logarithm of Net Worth with Net Worth of One or Less Shown at Zero



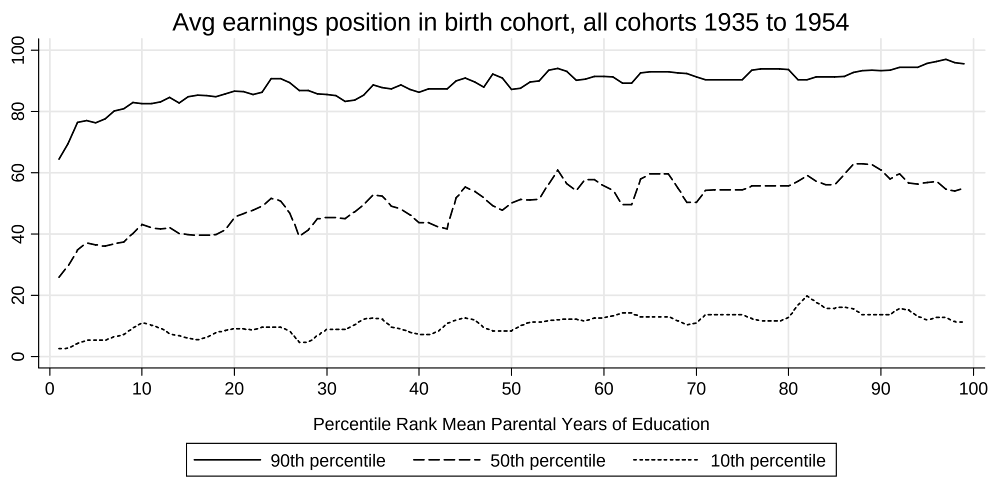
Source: Authors' tabulations from the Health and Retirement Study
Notes: Net worth is defined as the sum of financial assets (checking and savings accounts, CDs, stocks, bonds, mutual funds, IRAs, and Keogh accounts, money markets), homes, other properties and business assets less debt, including mortgages

Appendix Figure 5. Distribution of Educational Percentile Rank by Parental Education Percentile, Excluding Immigrant Children



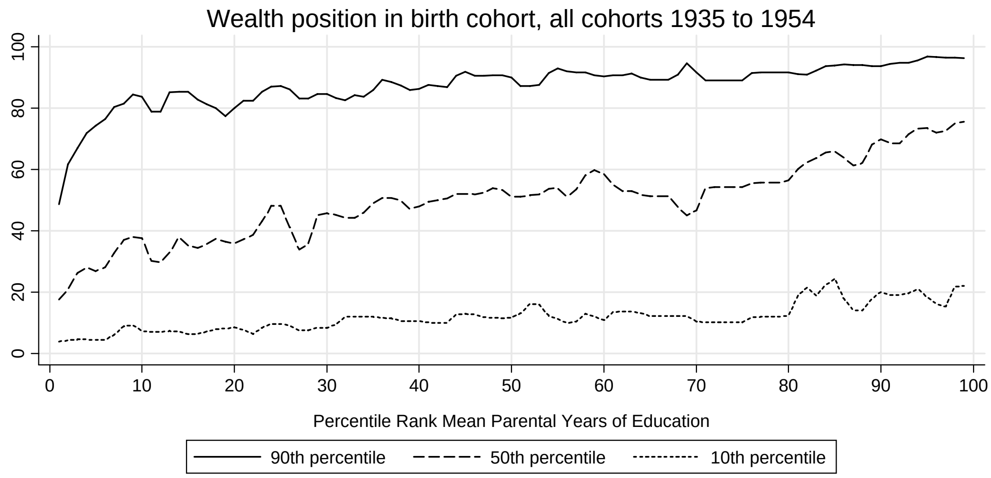
Source: Authors' tabulations from the Health and Retirement Study; estimates computed using local (kernel-weighted) quantile regressions of the within-cohort rank of outcome on the percentile rank of parent's education (average of mother and father) within cohort.

Appendix Figure 6. Distribution of Lifetime Earnings Percentile Rank by Parental Education Percentile, Excluding Immigrant Children



Source: Authors' tabulations from the Health and Retirement Study; estimates computed using local (kernel-weighted) quantile regressions of the within-cohort rank of outcome on the percentile rank of parent's education (average of mother and father) within cohort.

Appendix Figure 7. Distribution of Wealth Percentile Rank by Parental Education Percentile, Excluding Immigrant Children



Source: Authors' tabulations from the Health and Retirement Study; estimates computed using local (kernel-weighted) quantile regressions of the within-cohort rank of outcome on the percentile rank of parent's education (average of mother and father) within cohort.

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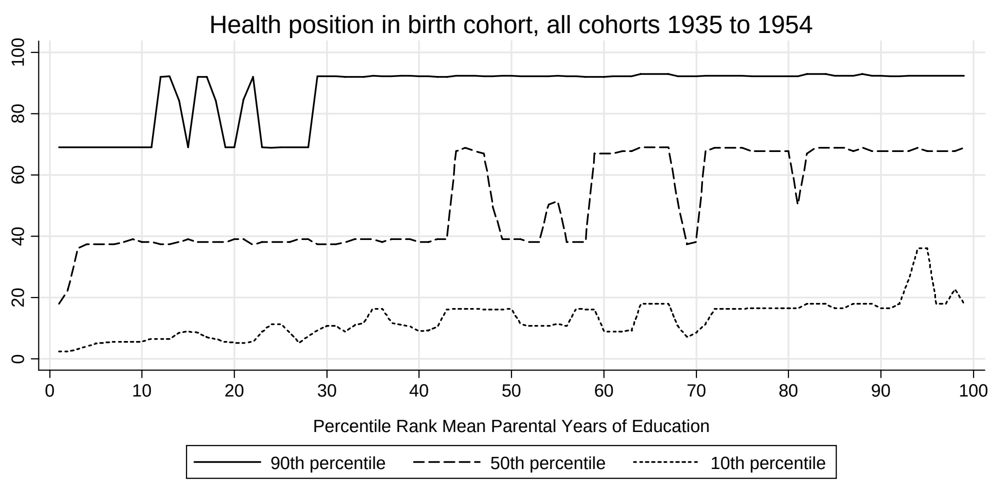

Source: Authors' tabulations from the Health and Retirement Study; estimates computed using local (kernel-weighted) quantile regressions of the within-cohort rank of outcome on the percentile rank of parent's education (average of mother and father) within cohort.

Endnotes

[1] This project was made possible by a grant from the Economic Mobility Project of the Pew Charitable Trusts. We gratefully acknowledge this support. We thank Gregory Acs, Harry Holzer, Julia Isaacs, Christopher Jencks and Scott Winship for helpful comments. Tom Hertz and Sheila Zedlewski also provided useful comments on earlier drafts.

[2] The full quote is [italics in original]: "If, as I have said, the things already listed were all we had to contribute, America would have made no distinctive and unique gift to mankind. But there has been also the *American dream*, that dream of a land in which life should be better and richer and fuller for everyone, with opportunity for each according to ability or achievement. It is a difficult dream for the European upper classes to interpret adequately, and too many of us ourselves have grown weary and mistrustful of it. It is not a dream of motor cars and high wages merely, but a dream of social order in which each man and each woman shall be able to attain to the fullest stature of which they are innately capable, and be recognized by others for what they are, regardless of the fortuitous circumstances of birth or position."

[3] Downward mobility is not a necessary side effect of upward mobility if the population is not held constant in some sense, since immigration can eliminate the balance between winners and losers, if everyone is allowed to be higher in the distribution than their parents. Differential mortality and fertility can also upset that balance, but the way that relative mobility is usually measured, i.e., comparing children's relative outcomes to those of their parents, minimizes these effects. If we compared all U.S. residents in the parent's generation, not all would have children, and many residents in their children's cohort would not have parents represented.

[4] For a discussion of the distinction between absolute and relative mobility, see for example Sawhill (2008).

[5] The intergenerational elasticity is defined as the marginal proportional change in children's outcomes for a small proportional change in parent's status, in expectation, e.g., the expected percent change gain in child's earnings for a one-percent increase in a parent's earnings. The correlation is the best linear prediction of standardized children's education given standardized parent's education—see Hertz et al. (2007).

[6] The horizontal and vertical coordinates in this graph are measured in log units (natural log of earnings, for example) rather than rank so the elasticity is the straight line that best fits the scatter plot, and is interpreted as percentage point changes, rather than standard deviation changes or percentile changes.

[7] When the ranks of children are not predictable from the ranks of parents, we must assess mobility in terms from one point of view using the slopes of conditional mean outcomes and from another using the slopes of quantiles, or in terms of whether the situation is such that one distribution can nonetheless be ranked as superior to the other ("stochastic dominance"). In broad terms, using the slopes of quantiles and measuring stochastic dominance are the same, but both are quite different from the conditional mean approach that traditional regression implies. If we care about the chance that the children with parents in the lowest part of the distribution can move into the top half of the distribution, we are measuring the quantile that crosses the 50 percent mark when the outcome variable is children's rank.

[8] Other studies explore related outcomes. For example, in addition to estimates shown in Table 1, Oreopoulos et al. (2004) estimated that an additional year of parental education lowers the probability that a child repeats a grade by five to eight percentage points. Bjorklund et al. (2004) reported that an additional year of maternal education increases the probability of her child going to university by as much as six percentage points. Chevalier (2004) estimated that an additional year of parental education increased the probability of the child attending a year beyond the compulsory schooling (lower) limit by four percentage points and instrumental variables (IV) estimates were twice as large.

[9] In some cases, authors find effects near zero, suggesting that we would not observe an association between parents' and children's education were education randomly assigned to parents. Black, Devereux and Salvanes (2005a), for example, conclude that extending middle school education to a previously underserved group of students had no causal impact on the educational attainment of most of the children of that group.

[10] Lindahl (2002) and Black, Devereux and Salvanes (2005b) point out that not only family size but birth order may matter to future earnings. In fact, it seems that birth order (or family size at birth) is more important than either completed family size or family size when a child is young, which undercuts many economic theories of why family size should have an impact on human capital transmission. Many authors have pointed out the effect on future health of low socioeconomic status, particularly at or near birth (see, e.g., Black et al. 1988 and Vågeröm and Illsley 1995; Kronstadt 2008 provides one review). It seems that much of this differential in adult health is not due to *absolute* economic well-being but *relative* well-being or rank (see Marmot et al. 1997 and other analyses of Whitehall data). Further, relatively little of the effect of parental socioeconomic status on health can be explained by differences in

behavior and observable characteristics (see, e.g., Marmot et al. 1997 and van de Mheen et al. 1998), though smoking and childhood nutrition may play a role. In short, the causal pathway is unclear (see also Smith 2004). Eriksson et al. (2005) suggested a large part of observed intergenerational transmission of earnings potential may be due to transmission of health status, though it is difficult to conclude much about directions of causation. Palloni (2006) similarly argues for reconsideration of the relative importance of health status to reproducing inequality.

[11] We could consider constructing causal estimates, for example by using IV by instrumenting for parental education using, for example, the GI bill, as in Page (2006), and for other factors such as parental health using, for example, exposure to epidemics, as in Almond and Mazumder (2005). However, the difficulties in interpretation of such estimates for our purposes (i.e., measuring mobility at a point in time for many subpopulations) far outweigh their usefulness in evaluating policy options (i.e., determining whether reduced form estimates are truly causal or mere association).

[12] Locally weighted linear regression smoothes across the range of outcomes at each quantile to a degree given by a bandwidth the researcher chooses. With a very large bandwidth, in the extreme, the outcome is a linear function of the predictor. With a very small bandwidth, in the extreme, there is no smoothing and the outcome is a discontinuous function of the predictor (a different value of the outcome for each distinct value of the predictor, so the function looks like a scatterplot). With an intermediate value, local regression allows some flexibility not allowed by a standard linear model but not the confusing detail of a scatterplot. A quantile regression, instead of modeling the mean outcome at some value of a predictor, models the Pth percentile of the outcome (for example, the 10th percentile, the median, or the 90th percentile). A standard quantile regression would show the median outcome for our models as a straight line; it would also be possible to run a quantile regression of the logit of children's outcomes on parental attribute so that the regression would show the median outcome as an ogive curve constrained to lie between zero and one. Our locally weighted quantile regression allows some semiparametric flexibility in order to discern what the true functional form might be, rather than imposing it by assumption.

[13] That is, they are at least age 16, the minimum age for labor force entry in 1951, when the earnings records start.

[14] Certain sectors of the labor force, including state workers who are covered by state pensions in select states, certain students and federal workers hired prior to January 1, 1984, are exempt from paying Social Security taxes. This excluded fraction has shrunk over time (in large part because of changing regulations about who is covered by OASDI), from about 17.5 percent of the civilian labor force in 1955 to about 4.0 percent early this decade (2002) (Committee on Ways and Means 2004). Non-covered state and local workers are concentrated in certain states, including Ohio, Massachusetts, Louisiana, Nevada, Colorado, California, Maine and Alaska, all of which had rates of less than half of state and local employees uncovered in 2001 (Ibid.).

[15] Note that all results are weighted to represent the sampling frame of the HRS, so results represent those who were born about 70 years ago and survived to at least age 51. Weighting mobility estimates by the surviving children ignores differential fertility by economic status and differential mortality, both of which may be important to parents who have fewer or more children than they would like or outlive their children but is standard practice in the mobility literature—it would be hard to estimate any other type of model.

[16] To avoid double counting, we use the latest valid observation for each person.

[17] Regressions of children's outcomes on mother's and father's education often reject the null of no difference in coefficients, but the difference in coefficients is substantively small and not uniformly favoring one parent. As Table 1 shows, estimates of the effect of mother and father's education on children's education are quite similar across a variety of studies.

[18] The measure is the count of activities of daily living with which the respondent reports any difficulty. The five activities included in this measure are walking across a room, eating, dressing, bathing/showering and toileting. There are modest differences in the question wording across HRS waves, so we suggest cautious interpretation.

[19] We use self-reported disability program participation, rather than reports from the administrative records, to maximize sample size.

[20] The test of mortality prediction was the extent to which the index boosted explanatory power in logistic regressions, estimated separately by sex, with controls for age, education, race and period. The regressions were estimated using the HRS data on all person-year observations.

[21] This is not the optimal way to test for the effects of immigration. We would prefer to compare to graphs in which the *parents* were native-born, but such data are not readily available.

[22] These analyses have some significant limitations. First, they are restricted to individuals who survive until at least age 51 (the point of the HRS sample frame). Second, as indicated, we use first children in the analyses; if the education of first children is not representative of that of all children, then the estimates may be biased. Third, there

is censoring in the children's reports, as many HRS respondents are continuing to have children (or their children have not reached the age 25, the age we established as the lower bound for our analyses). We thus suggest that the reader interpret these results cautiously. However, the rarity of the opportunity these data present us with suggests that these results are still worth consideration.

[23] We could also compute the ratio of observed to expected proportions, where numbers greater than one would show excess persistence, but the columns would no longer sum to one hundred percent and would no doubt confuse those readers used to transition matrices.