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The Decline in Intergenerational Mobility After 1980

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Abstract

We demonstrate that intergenerational mobility declined sharply for cohorts born between 1957 and 1964 compared to those born between 1942 and 1953. The former entered the labor market largely after the large rise in inequality that occurred around 1980 while the latter entered the labor market before this inflection point. We show that the rank-rank slope rose from 0.27 to 0.4 and the IGE rose from 0.35 to 0.51. The share of children whose income exceeds that of their parents fell by about 3 percentage points. These findings suggest that relative mobility fell by substantially more than absolute mobility.

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I. Introduction

One of the most notable changes in the US economy in recent decades has been the rise in inequality. A key inflection point in inequality appears to be around 1980. It was during the early 1980s that there was a pronounced increase in the 90-10 income gap and a sharp rise in the income share of the 1 percent (see Figure 1). It was also during this period that consumption inequality rose (Meyer and Sullivan, 2013) and the labor market returns to education began to increase dramatically (Goldin and Katz, 1999). With the advent of a more unequal society, concerns about a possible decline in inequality of opportunity have risen to the forefront of policy discussion in the US.

To better understand inequality of opportunity, economists and other social scientists have increasingly focused attention on studies of intergenerational mobility. These studies typically estimate the strength of the association between parent income and the income of their offspring as adults. If the strength of the association is high, it suggests that there may be a low degree of relative intergenerational mobility as a family's position in the income distribution is largely replicated from one generation to the next. In contrast, if intergenerational associations are relatively small, then we might infer that there is a high degree of mobility as families are more likely to move up and down the income distribution. At this point, there is a fairly clear consensus that rates of intergenerational income mobility in the US are relatively low compared to other advanced economies (Black and Devereaux, 2011).

One important question is whether this has always been the case. Between 1948 and 1973, for example, the U.S. economy experienced a long period of relatively rapid economic growth and was characterized by much lower inequality and lower returns to education than in the period since. One might wonder whether intergenerational mobility might have been much more rapid for individuals who entered the labor market during this so-called "golden age". Interestingly, there is very little evidence on this point. Only a few studies have attempted to study changes over time in intergenerational mobility in the U.S. and have produced seemingly conflicting results. However, most of these studies have not been able to track individuals who entered the labor market during this golden age of economic prosperity and before the inflection point in inequality.

We present new evidence using the National Longitudinal Surveys (NLS) and document a sharp decline in intergenerational mobility between two groups of cohorts. The first were born between 1942 and 1953 and the second were born between 1957 and 1964. The former entered the labor market prior to the large rise in inequality that occurred around 1980 while the latter cohorts entered the labor market largely after this inflection point in inequality.

We measure the intergenerational association using the rank-rank slope in family income (Chetty et al, 2014A), the intergenerational elasticity (IGE), and the persistence in earnings and earnings normalized by average earnings in the population. The rank-rank slope is a measure of positional mobility and provides the rate of intergenerational persistence in ranks. A higher slope indicates greater persistence and less mobility. We show that the rank-rank slope rose from 0.27 to 0.4 across these two cohort groups. A well-known finding based on the work of Chetty et al (2014A) is the large amount of geographic dispersion in rank mobility across the U.S. Our findings suggest that the time variation in rank mobility is of a similar magnitude to this geographic variation. For example, if we use the city level (MSA) estimates from Chetty et al (2014A) that characterize mobility for US cohorts born between 1980-1982, our findings suggest that the cross-cohort decline in mobility is the equivalent of moving from around the 14th percentile city to the 86th percentile city.[1] We similarly see substantial increases in our measures of

[1] See Chetty et al's (2014A) online table 4 that presents estimates for 381 MSAs.

intergenerational persistence in log income (the IGE), level of income, and normalized income.

These findings are largely consistent with the prior literature. Aaronson and Mazumder (2008) create a time series of intergenerational elasticity from 1940 through 2000 by using a group-based estimator with historical Census data. They document a pronounced decline in mobility between 1980 and 1990 that is consistent with the inflection point in inequality described earlier. In particular, their time series pattern shown in Figure 2 closely matches patterns in the returns to college data as estimated by Goldin and Katz (1999). This is notable because theoretical models (e.g. Solon, 2004) would predict exactly such a correspondence between changes in intergenerational mobility and the returns to schooling. Furthermore, two other studies (Bloome and Western, 2011; Levine and Mazumder; 2007) using the same National Longitudinal Surveys have documented similar declines in mobility-related measures.

Our findings are also consistent with those of Chetty et al (2014B). For example, they find that the rank-rank income association for 30 year-olds (born between 1970 and 1982) has been relatively constant between 2000 and 2012. To put this finding in perspective, we extend the Aaronson and Mazumder (2008) results by adding data from the 2008-2012 ACS to create an average data point for 2010. We also find that intergenerational mobility and the returns to college has been roughly flat over the 2000 to 2010 period.[2] However, none of the empirical results in Chetty et al (2014B) address whether mobility changed around the inflection point in inequality around 1980 since their tax data do not extend that far back in time.[3] Hilger (2016) uses historical Census data to estimate long-run trends

[2] Autor (2014) also finds that the rate of return to college has been flat between 2000 and 2012.

[3] Some other studies using the PSID (Hertz, 2007; Lee and Solon, 2009) have also found that the intergenerational elasticity has been roughly constant in recent decades. Chetty et al (2014B) conclude that if that one combines their results covering cohorts born since 1970 with those of Lee and Solon (2009) it suggests that there has been no change in intergenerational mobility in the

in a different concept of intergenerational mobility, *educational* mobility, and finds evidence of a decline after 1980.

We also examine trends in absolute intergenerational income mobility. Similar to Chetty et al (2016), we define absolute intergenerational income mobility as the share of children whose income exceeds that of their parents. Our preferred estimates show absolute mobility declined 3 percentage points between the 1942-1953 cohort and the 1957-1964 cohort. This is much smaller than the 21 percentage point decline suggested by Chetty et al (2016)'s baseline results which rely on an assumption that the copula relating parent and child income remained constant for cohorts born between 1940 and 1970. Our results suggest this is not the case.

II. Data

Our primary data sources are the National Longitudinal Surveys of Older Men and Young Men and Mature Women and Young Women (NLS66) and the National Longitudinal Survey of Youth 1979 (NLSY79). We construct our samples to maximize comparability across these two surveys.

The NLS66 separately sampled young men who were 14 to 24 years old on March 31, 1966, young women who were 14-24 on December 31, 1967, older men who were 45-59 on March 31, 1966, and older women who were 30-44 as of March 31, 1967. The different surveys frequently include respondents from common households. We create two sets of mobility measures: one with the available 782 father-son pairs and another with 697 father-daughter pairs. We measure childhood total family income using reports of prior year income from 1966, 1967, and 1969 measured in the Older Men surveys when fathers were 44 to 62 years old, daughters

second half of the 20th century. However, it is not clear that one can simply combine the results from completely different data sources that use entirely different concepts of mobility. Further, as we discuss below, the PSID is not well suited to detecting a change in intergenerational mobility around 1980.

were 12 to 26, and sons were 13 to 27.[4] We measure daughters' adult family income using the average of all available total family income reports from the 1991, 1993, 1995, 1997, 1999, and 2001 Young Women surveys when the daughters were 37 to 58 years old. Finally, we measure sons' adult family income using all available total family income reports from the 1977, 1979, and 1980 Young Men surveys when sons were 25 to 39 years old.

An important point to highlight is that unlike the Young Women's survey which continued through 2000, the Young Men's survey was discontinued nearly 20 years earlier in 1981. Therefore, for the NLS66 samples, we are only able to observe sons relatively early in their career at an average of around 31. In contrast, we can follow daughters into the prime of their careers at an average age of around 48. Due to life cycle bias, intergenerational rank-rank slopes are typically lower when children are measured early in their career rather than during the prime of their life cycle (Mazumder, 2016). Therefore, our preferred analysis uses father-daughter pairs since we observe income during prime earning years in both generations and for both cohort groups. However, we also show the estimates for the father-son pairs where we only have "early career" estimates for the NLS66 sample where we expect life cycle bias to attenuate the estimates.

For the NLSY79, we combine a nationally representative cross-sectional sample of 6,111 individuals and an oversample of 5,295 Hispanic, Black, and economically disadvantaged non-Black, non-Hispanic individuals designed to be representative of the population born between 1957 and 1964 and living in the United States in 1979.

From the full data, we construct two samples designed to match the NLS66 father-son and father-daughter pairs. We restrict our NLSY79 father-daughter sample to female respondents whose fathers were between 22 and 46 years old at

[4] We limit fathers' income to three years to make the analysis parallel with the NLSY79 where we observe three years of family income as described later.

their daughter's birth. This father age restriction matches the age range of fathers in our NLS66 father-daughter sample. This restriction is necessary since father age is restricted in the NLS66 by the NLS66's Older Men and Younger Women sampling frames. We restrict our NLSY79 father-son sample to male respondents whose fathers were between 21 and 43 at their son's birth.

We use the same childhood income measures in both the father-son and father-daughter samples. When youth were still living with their parents, their parents were asked to report total family income from the previous year in the 1979, 1980, and 1981 surveys. We use the average of all the non-missing family income reports, up to three years, less any income of the youth as our childhood family income measure. Youth were 14 to 23 years old during these years.

Our adult income measures differ across the NLSY79 father-daughter and father-son samples. For the father-daughter sample, we use the average of all non-missing measures of total family income in 2001, 2003, 2005, 2007, 2009 and 2011 surveys when the women were 37 to 54 years. For the father-son sample, we use the average of all non-missing measures of total family income in 1990, 1991, and 1993 when the men were 26 to 36 years old in order to mimic the data restriction in our NLS66 sample. However, we also produce a set of estimates using sons at their prime age to show what we would estimate if we used the same measurement approach that we use for daughters in the NLSY79.

We weight all of our analysis using the child's survey weight in the first round of the survey.

Table 1 shows summary statistics for the NLS66 and NLSY79 father-daughter and father-son samples. Panel A shows estimates for the 697 NLS66 father-daughter pairs with daughters born between 1942 and 1953. On average, fathers' family income when fathers were around 40 years old and daughters were around age 19 was $80,500 (all income in 2015 dollars). When the daughters were around 48 years old, their average income was $102,198. Panel B shows analogous estimates for the 1,363 father-daughter pairs in the NLSY79 with daughters born between 1957 and 1964. Family income when fathers were about 48 and daughters were about 19 was \$81,537, or about 1% higher than in the NLS66 cohort. When daughters were around 47 their average family income was \$101,294.

Panels C and D show estimates for the 782 NLS66 and the 1,353 NLSY79 father-son pairs, respectively. For the NLS66 father-son pairs, fathers' average family income when fathers were about 51 and sons were about 18 was \$78,977. Sons' average family income when they were about 31 years old was \$75,414. For the NLSY79, fathers' family income when fathers were about 47 and sons were about 18 was \$83,552. When sons were about 30, their average income is \$92,951.

Estimated density functions for the NLS66 and NLSY79 parent and daughter family income distribution are shown in Appendix I. For comparison, densities for comparable samples drawn from the Current Population Survey's (CPS) Annual Social and Economic Supplement are also shown. These figures suggest our samples are positively selected on income. Appendix II shows that our substantive findings are largely unaffected if we re-weight our sample to match the CPS income distributions.

III. Methods

We estimate summary measures of intergenerational mobility in the NLS66 and NLSY79 using the following regression:

$$M_{1is} = \alpha + \beta \times I_{is} + \gamma^{NLS66} M_{0i} \times (1 - I_{is}) + \gamma^{NLSY79} M_{0i} \times I_{is}, \qquad (1)$$

where i indexes father-child pairs and s denotes pair i's survey. M_0 and M_1 are income measures for the parent and child generations, respectively, I_s is an indicator for being in the NLSY79 sample, and γ^{NLS66} and γ^{NLSY79} are estimates of intergenerational mobility for the NLS66 and NLSY79, respectively.

In order to provide a robust picture of intergenerational mobility in both sets of cohorts, we use four different measures of income which correspond to four different measures of intergenerational mobility. First, we measure income using parent and child rank in their respective generation's income distribution. In this case, the coefficients γ^{NLS66} and γ^{NLSY79} are interpretable as rank-rank slopes for the NLS66 and NLSY79 cohorts, respectively. Second, we use log income. Here, γ^{NLS66} and γ^{NLSY79} represent the intergenerational elasticity (IGE) for each cohort. In this case, the small number of father-child pairs with negative or zero total family income are dropped from the analysis. Third, we use income directly. The γ coefficients are interpretable as the rate of mean reversion in income among each set of cohorts. Fourth, we use total family income measured in units of average family income in each cohort's parent or child generation. Like ranks, this is a relative income measure. But unlike ranks, this measure captures the fact that the magnitude of income differences changes across the income distribution.

In addition to these four regression based mobility measures, we also report the share of children whose income exceeds that of their parents. This is the focal mobility measure in the related study by Chetty et al (2016). We take two approaches to ensure that family income is comparable in the parent and child generations. First, we estimate rates of absolute mobility with a parametric adjustment for differences in fathers' and daughters' average age when income is measured by controlling for separate quartic polynomials in the difference between fathers' and daughters' average ages across the years their income is measured for the NLS66 and NLSY79 cohorts. Second, we estimate absolute mobility among the subsample of father-daughter pairs where the absolute value of the difference between fathers' and daughters' average age across the years their income was measured is no greater than 4 years, 3 years, 2 years, and 1 year.

IV. Results

Relative Mobility

Estimates of γ^{NLS66} and γ^{NLSY79} from equation (1) above are shown in Table 2. Panel A shows estimates for matched father-daughter pairs. These are our preferred estimates since they include income during prime earning years for both cohorts because the NLS66's cohort of young women was followed until 2003, whereas sons' income is limited to early career earnings because the NLS66's young men cohort was only followed until 1981.

Column 1 shows estimates when M_0 and M_1 denote child and parent rank in their cohort's parent and child income distributions, respectively. $\hat{\gamma}^{NLS66}$, which is interpretable as the rank-rank slope among father-daughter pairs in the NLS66, is 0.27. In contrast, the rank-rank slope among NLSY79 father-daughter pairs, $\hat{\gamma}^{NLSY79}$, is 0.40, which indicates a nearly 50 percent increase in persistence in relative ranks across generations between the two cohorts. These rank-rank relationships are shown in Figure 3. As a benchmark, we can compare these rank-rank slopes to estimates by city (MSA) reported in Chetty et al (2014A). The rank persistence for cohorts born between 1942-1953, 0.27, corresponds to the 55th most mobile city out of the 381 cities (about the 14th percentile) in Chetty et al (2014A)'s data. Among the NLSY79 cohorts, born just over a decade later, rank persistence corresponds to the 327th most mobile city (about the 85th percentile). The difference between rank persistence across these two cohorts is statistically significant at conventional levels ($p = 0.01$).

Column 2 shows estimates of the IGE in both cohorts. As with rank persistence, we also see a large and statistically significant ($p = 0.02$) increase in the IGE across the two cohorts, from 0.35 for the NLS66 cohorts to 0.51 for the

NLSY79 cohorts. Columns 3 and 4 show estimates of persistence in the level of family income and in normalized income, respectively. Based on these measures, persistence increased by 51% and 55%, respectively. Both of these differences are statistically significant at conventional levels ($p = 0.05$ and $p = 0.04$, respectively).

Panel B shows analogous estimates for father-son pairs in the NLS66 and NLSY79. While the father-daughter estimates are our preferred estimates, we similarly find a substantively large, and in most cases statistically significant, increase in persistence between the two cohorts regardless of which measure we use.

We construct our NLSY79 father-son sample in order to best match the features of NLS66's father-son pairs. In order to demonstrate the impact of these features on the estimates, we show a second version of estimates for the NLSY79 father-son pairs using the income measures used for the father-daughter analysis. Consistent with Mazumder (2016) we find that using income during prime earning years instead of early career income increases the estimates of rank persistence, the IGE, and income persistence increase by 15-22%. On the other hand, persistence in normalized income declines slightly from 0.53 to 0.51 when prime age income is used.

We find that the declines in relative mobility are highly robust to reweighting our sample to match the income distributions in the CPS. Given the similarity of the results, we show these results in appendix Table A2.

Absolute Mobility

Table 3 shows estimates of the share of daughters whose family income exceeded that of their fathers in each of the cohorts. Among our main sample of daughters in the NLS66 born between 1942 and 1953, 61 percent of daughters' family incomes exceeded that of their fathers, whereas only 58 percent of daughters in the NLSY79 had family income higher than their fathers' family income. This 3 percent decline in absolute mobility is not statistically significant at conventional levels (p=0.31).[5]

In order for absolute mobility calculations to be valid, the income measures for parents and children must be comparable. As a result, one may be concerned that, on average, fathers are several years older when their family income is measured than when daughters' adult family income is measured. We address this concern in two ways. In column 2, we show how the estimates change if we control for separate quartic polynomials in the difference between average father and daughter age in the years their incomes are measured for the two cohorts. With this regression adjustment, the estimates are interpretable as the rate of absolute mobility among father-daughter pairs where fathers and daughters were the same age, on average, in the years their family incomes were measured. Here, we see no difference in absolute mobility. 58 percent of daughters in both the NLS66 and NLSY79 cohorts had total family income which exceeded that of their fathers, respectively.

The estimates in column 2 depend on the parametric assumption that the rate of absolute mobility is a quartic function of the difference between father and daughter age when income is measured. In the remaining four columns of Table 3, we adjust for age differences more non-parametrically by imposing increasingly

[5] Although the NLS data is subject to topcoding that varies by survey, year and income concept, the rates of topcoding are typically very low and often less than 1 percent. Nevertheless, to show that topcoding is not driving our results, we re-estimated our results under the assumption that any daughter whose own earnings or business income, spouse's earnings or business income, or family capital returns were top coded in any of the six years included in our measure of average family income automatically exceeded their parents' income. We found that 62 percent of daughters in the NLS66 and 59 percent of daughters in the NLSY79 had family income which exceed that of their parents.

strict sample restrictions to limit the difference between fathers' and daughters' ages when income is measured. Columns 3 through 6 restrict our sample to father-daughter pairs where the difference between fathers' and daughters' average age in the years their income is measured is no greater in absolute value than 4 years, 3 years, 2 years, or 1 year, respectively. However, this comes at the cost of throwing away a significant amount of the data and decreasing precision. When we impose the age difference restriction, the absolute mobility change ranges from zero, when ages are constrained to be no more than 2 years apart, to 5 percentage points when ages are constrained to be no more than 1 year apart. However, with the 1 year age difference restriction, we have fewer than 100 father-daughter pairs in each cohort group and the standard errors are much larger. Overall, however, in no case is the change in absolute mobility significantly different from zero at conventional levels.

Unlike the case with relative mobility, re-weighting our sample to match the CPS's income distributions does affect our absolute mobility estimates. Table 4 shows that the decline in absolute mobility increases after re-weighting and in some cases becomes statistically significant.

Overall, we conclude that there is reasonable evidence that absolute mobility also declined but not nearly as much as relative mobility. Our preferred baseline estimates shown in columns 1 and 2 of Table 3 suggest that there was only a modest 1 to 3 percentage point decline in absolute mobility that was not statistically significant. The analogous declines in columns 1 and 2 of Table 4, which uses our sample re-weighted to match the CPS income distributions, appear to be larger, in the range of 5 to 6 percentage points. Nevertheless, these estimates are much smaller than the 21-percentage point decline implied by the baseline estimates in Chetty et al (2016).[6]

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[6] The 21 percentage point estimate is based on the difference in the average levels of absolute mobility between NLS66 and NLSY79 cohorts in their "Baseline Estimates" shown in their Figure

V. Discussion

Relative Mobility

Viewed through the appropriate lens, our finding of a decline in intergenerational mobility over the second half of the 20th century is reasonably consistent with the previous literature. Aaronson and Mazumder (2008) provide a useful framework for considering our results and those of the existing literature. Figure 2 plots a replication of their estimates of the intergenerational elasticity using Census data from 1940 to 2010.[7] Their estimates use a group-based estimation strategy where the average income of groups of individuals defined by state and year of birth is linked to the average income of a synthetic group of parents in a prior Census who had children in the same state and year. Importantly these estimates are plotted by the year of income of the child and not by their birth year. They document an increase in intergenerational mobility after 1940 and a decline after 1980 that closely tracks the changes in the return to college.

Our earlier cohorts, born between 1942 and 1953 entered the labor market during the 1960s and 1970s, well before the increase in inequality around 1980. The latter group of cohorts, born between 1957 and 1964 in contrast, largely entered the labor market after the pronounced rise in inequality.[8] It is worth noting that Bloome and Western (2011) also document a significant increase in the intergenerational elasticity in income across these same cohort groups. Similarly,

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2.A. This calculation used data from "Online Data Table 1" downloaded from http://www.equality-of-opportunity.org/data/ on February 27th, 2017.

[7] While we follow Aaronson and Mazumder (2008) and label the results by the year of the Census, the estimates are actually based on income measured in the year prior to the Census.

[8] If most individuals enter the labor market between the ages of 18 and 25, this would imply that the 1942 to 1953 cohorts entered the labor market between 1960 and 1975 and that the 1957 to 1964 cohorts entered the labor market between 1975 and 1989.

Levine and Mazumder (2007) show that the sibling correlation in log wages, log annual earnings and log family income rose by a similar amount between the NLS66 and NLSY79.

Seemingly at odds with our findings are the results of Hertz (2007) and Lee and Solon (2009) who show relative stability in IGE trends using the PSID. However, the structure of the cohorts of the PSID is not ideally suited to picking up changes in the IGE around the inflection point in inequality in 1980. Since the PSID begins in 1968, we cannot observe a representative group of children born in the 1940s living at home with their parents. We can observe cohorts born starting around 1951 who would have been 17 at the time of the very first PSID survey. However, this implies we would observe very few of our earlier group of NLS66 cohorts in the PSID. Further, the small samples in the PSID also produce much noisier cohort by cohort estimates making it harder to rule out a change in trend for the specific cohort groups we examine.[9] Finally, given the well-known issues of lifecycle bias in estimating the IGE, a reliable estimate of the IGE for the 1951 cohort that would be free of lifecycle bias would not be possible until around 1990 which is after the rise in inequality.[10]

The empirical results from Chetty et al (2014B) are easily reconciled with our findings as they only report estimates of intergenerational income mobility over the 2001 to 2012 period using cohorts born from 1971 through 1982 and observed at age 30. These individuals would have entered the labor market starting in the late 1980s at the earliest. Our replication of Aaronson and Mazumder (2008) shows relative stability in intergenerational mobility between 2000 and 2010 (Figure 2). Furthermore, if we replicate Goldin and Katz's estimates of the return to college

[9] For example, the point estimates of the IGE in Lee and Solon (2009) for women observed in the years 1977 through 1979 range from 0.05 to 0.20 with standard errors between 0.12 and 0.17.
[10] Hertz (2007) and Lee and Solon (2009) address life cycle bias by using model based approaches that rely on the assumption that life-cycle bias is unchanging over time. In our data we can directly observe our cohort groups during the prime of their life cycle.

we similarly find relative stability from 2000 to 2010. Autor (2014) also finds relative stability in the returns to college over the same period using annual CPS data.

Although we find these coincident patterns between changes in relative intergenerational mobility and changes in inequality very intriguing, we urge some caution in interpreting these trends. First, the changes could be driven by other contemporaneous factors, including changes in marital patterns, women's labor force participation, neighborhood social capital, or government social programs just to name a few potential candidates. A thorough assessment of the causes of the change in intergenerational mobility is beyond the scope of the current study and is an important topic for further research.[11] We also note that Nybom and Stuhler (2016) show that changes in intergenerational mobility may not even necessarily reflect contemporaneous events and in principle, could be due to changes in policy or the economic environment that occurred well in the past.

Absolute Mobility

Our results are at odds with the recent striking results concerning trends in absolute mobility from Chetty et al (2016) who document a sharp decline in the fraction of individuals whose income levels surpass that of their parents for cohorts born since 1940. Chetty et al (2016) do not actually use micro-level intergenerational data but instead indirectly infer rates of absolute mobility by combining information on the copula of the joint distribution of parent and child income for cohorts born between 1980 and 1982 with data on the marginal income

[11] Although our data is not ideally suited for investigating mechanisms, we did some simple analysis of the possible role of marriage. Like the recent work by of Gihleb and Lang (2016), we find no difference in educational assortative mating across the two cohorts. We did find evidence of a stronger association between parent's rank in the income distribution and marriage rates in the later cohort.

distributions in each generation for cohorts born since 1940. Their analysis begins by assuming that the copula is constant going back in time but they proceed to argue that their qualitative finding of a sharp decline in absolute mobility is not appreciably affected by the copula and is driven by the dramatic changes in the marginal distributions. Our analysis, in contrast, uses actual intergenerational data and provides direct evidence on how exactly the copula changed for our cohort groups. We also find evidence of a decline in absolute mobility, but our estimates suggest their benchmark estimates likely overstate the decline in absolute mobility. In fact, our largest estimate among those that use all the data, shows a 6 percentage point decline, is less than a third of their baseline estimate.

VI. Conclusion

The US economy in the thirty years following the end of World War II was characterized by relatively rapid growth and low inequality. By many measures, inequality appeared to surge after 1980. We document that cohorts who entered the labor market well before this rise in inequality experienced significantly higher rates of intergenerational mobility than those who entered the labor market during or afterwards. This is true for several measures of relative mobility including the rank-rank slope and the intergenerational elasticity. The decline in mobility is similar in magnitude to the extent of geographic variation in rank persistence across the U.S. We also document a decline in absolute mobility for these same cohorts but show that it is much smaller than the decline in relative mobility. We find that the decline in absolute mobility is also dramatically smaller than the baseline estimates of Chetty et al (2016). An important topic for future research is to better understand the sources behind the changes in intergenerational mobility we document.

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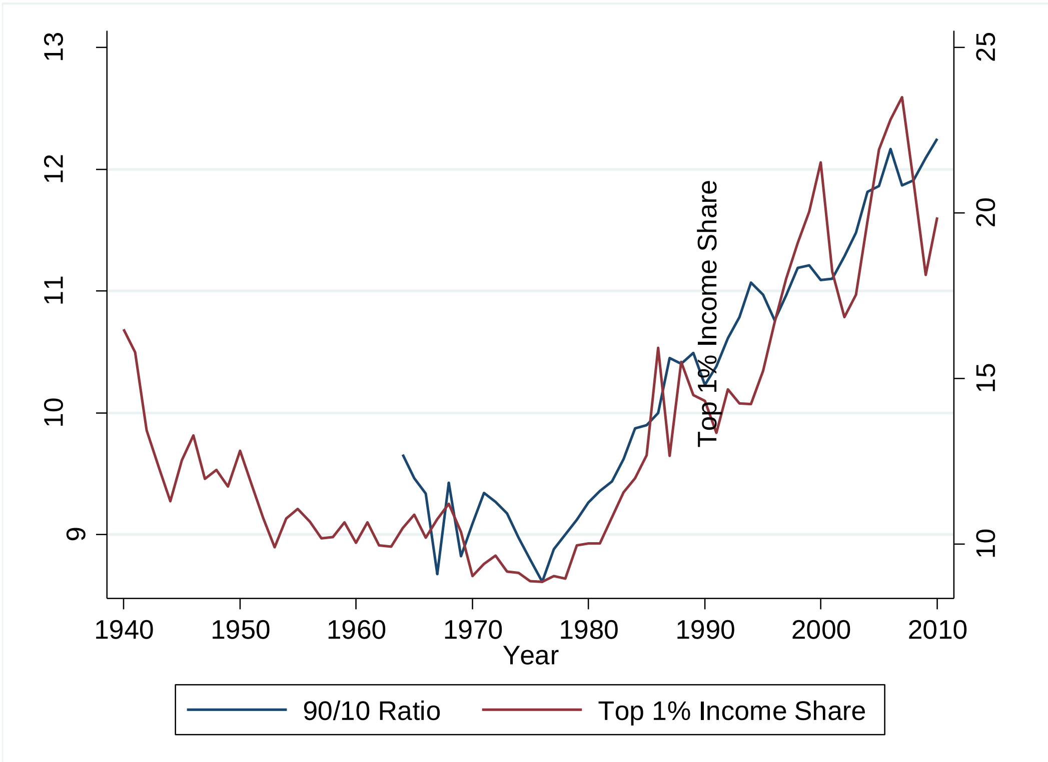
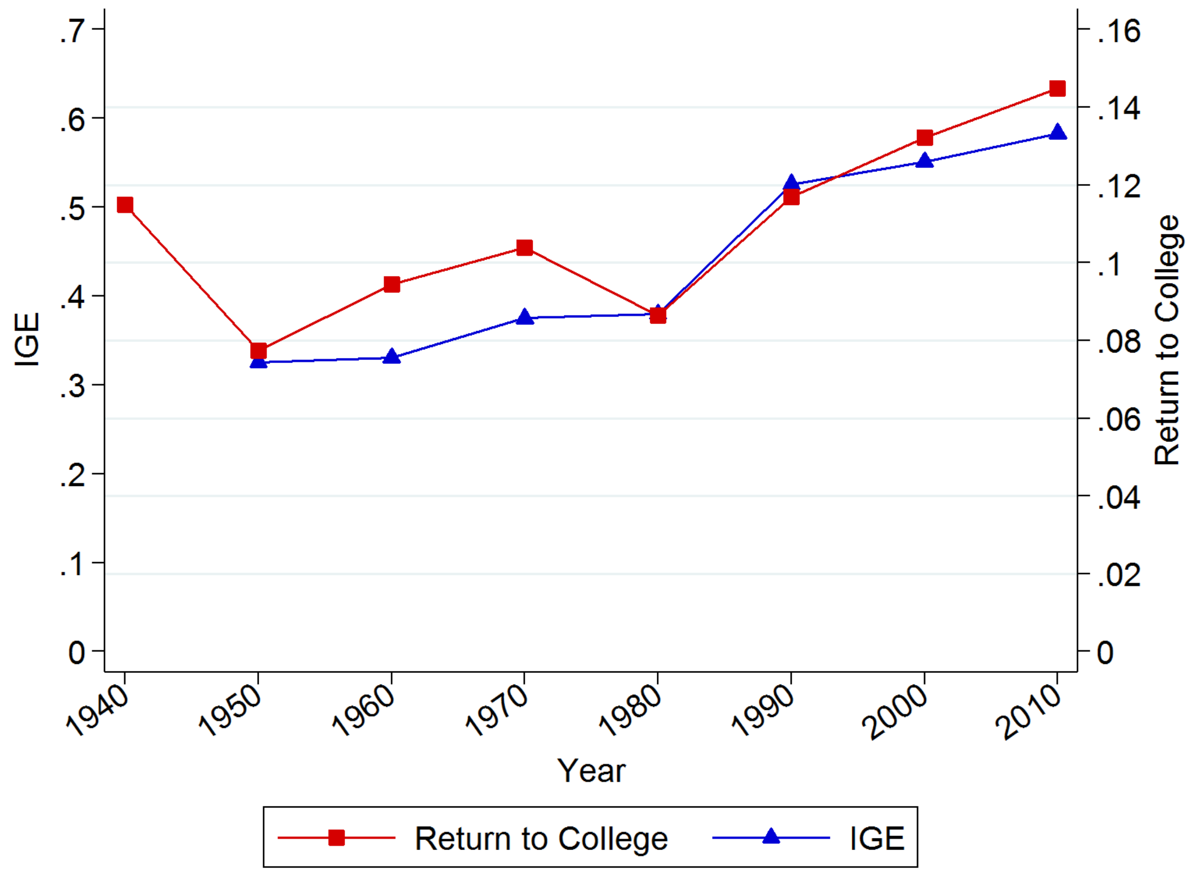
Figure 1. 90/10 Ratio and Top 1% Income Shares, 1940-2010



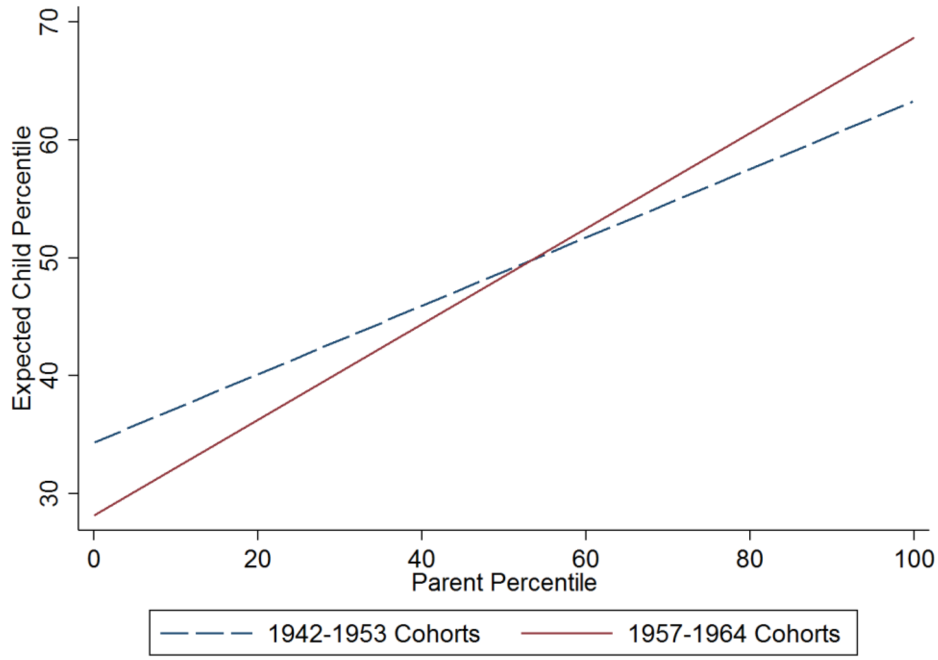
Notes. 90/10 ratio based on authors' calculations using Current Population Survey Annual Social and Economic Supplement data from 1964 to 2010. Estimate are based on average pre-tax family income among the sample of household heads weighted by the supplement weights. Top 1% income shares based on estimates reported in Piketty and Saez (2003). The updated series was downloaded from The World Wealth and Income Database (Alvaredo et al) on December 20th, 2016.

Figure 2. Trends in the IGE and Returns to College



Notes. Authors' replication of Aaronson and Mazumder (2008), Figure 4.C extended to include 2010. Return to college estimated using the methodology of Goldin and Katz (2009), also extended to 2010. All calculations use decennial census and ACS data.

Figure 3. Rank Mobility among Father-Daughter Pairs with Daughters Born Around 1948 and 1960



Notes. Based on authors' calculations using NLS66 and NLSY79 father-daughter pairs.

Table 1. Summary Statistics for NLS66 and NLSY79 Samples

	Mean	SD	Min	Max
A. NLS66 Father-Daughter Pairs (N=697)				
Parent Income Around Age 19 (2015$)	80500	55968	-1460	426097
Adult Income Around Age 48 (2015$)	102198	74591	-7255	435492
Father Birth Year	1915.54	3.83	1906	1921
Child Birth Year	1948.93	2.82	1942	1953
B. NLSY79 Father-Daughter Pairs (N=1,363)				
Parent Income Around Age 19 (2015$)	81537	46679	-35371	272445
Adult Income Around Age 47 (2015$)	101294	83687	0	554337
Father Birth Year	1931.44	5.37	1920	1942
Child Birth Year	1961.18	2.13	1957	1964
C. NLS66 Father-Son Pairs (N=782)				
Parent Income Around Age 18 (2015$)	78977	47861	2148	426097
Adult Income Around Age 31 (2015$)	75414	39650	-5772	257897
Father Birth Year	1915.15	3.92	1906	1921
Child Birth Year	1947.63	2.69	1941	1952
D. NLSY79 Father-Son Pairs (N=1,353)				
Parent Income Around Age 18 (2015$)	83552	49523	-44590	272445
Adult Income Around Age 30 (2015$)	92951	122080	0	813634
Father Birth Year	1931.74	5.75	1920	1943
Child Birth Year	1961.19	2.13	1957	1964

Table 2. Mobility in NLS66 and NLSY79 Father-Daughter and Father-Son Pairs

	Rank-Rank	IGE	Income	Normalized Income
	Panel A. Father-Daughter Pairs			
1942-1953 Cohorts, Prime Income	0.27	0.35	0.39	0.31
(NLS 66)	(0.04)	(0.05)	(0.07)	(0.06)
1957-1964 Cohorts, Prime Income	0.40	0.51	0.59	0.47
(NLSY79)	(0.03)	(0.04)	(0.07)	(0.06)
H_0: Measures Equal, p=	0.01	0.02	0.05	0.04
	Panel B. Father-Son Pairs			
1942-1953 Cohorts, Early Career Income	0.26	0.24	0.23	0.24
(NLS 66)	(0.04)	(0.04)	(0.04)	(0.05)
1957-1964 Cohorts, Early Career Income	0.33	0.37	0.59	0.53
(NLSY79)	(0.03)	(0.04)	(0.11)	(0.10)
H_0: Measures Equal, p=	0.15	0.02	0.00	0.01
1957-1964 Cohorts, Prime Income	0.38	0.45	0.69	0.51
(NLSY79 - Daughter Sampling)	(0.03)	(0.04)	(0.08)	(0.06)

Notes. The NLS66 sample includes 697 father-daughter pairs and 782 father-son pairs. The NLSY79 sample includes 1,363 father-daughter pairs and 1,353 father-son pairs. The Column 2 samples include 673 and 771 father-daughter and father-son pairs from the NLS66, respectively, and 1,349 and 1,336 father-daughter and father-son pairs from the NLSY79, respectively. Incomes measured in 2015 dollars. Robust standard errors in parenthesis.

Table 3. Absolute Mobility Among NLS66 and NLSY79 Father-Daughter Pairs

			Father-Daughter Average Age Within:			
	Main Sample	Regression Adjustment	4 Years	3 Years	2 Years	1 Year
1942-1953 Cohorts, Prime Income	0.61	0.58	0.59	0.6	0.61	0.61
(NLS 66)	(0.02)	(0.04)	(0.03)	(0.03)	(0.04)	(0.06)
1957-1964 Cohorts, Prime Income	0.58	0.58	0.57	0.57	0.61	0.56
(NLSY79)	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)	(0.06)
H_0: Measures Equal, p=	0.31	0.85	0.68	0.44	0.99	0.5
Average Age in Years Income Measured						
NLS66 Fathers	50.9	50.8	48.4	48.3	48.1	48.1
NLS66 Daughters	46.2	46.1	47.4	47.8	48.0	48.2
NLSY79 Fathers	47.6	47.6	45.0	44.9	44.8	44.9
NLSY79 Daughters	44.8	44.8	44.9	44.9	44.8	44.9
NLS66 Pairs	697	697	301	226	157	82
NLSY79 Pairs	1363	1363	685	522	321	93

Notes. Estimates show proportion of children in NLS66 and NLSY79 cohorts whose income was higher than that of their parents. The regression adjustment includes separate quartic polynomials in the difference between average father age and average daughter age in the years income is measured. Incomes adjusted to 2015 dollars using CPI for all urban consumers. Robust standard errors in parenthesis.

Table 4. Re-Weighted Absolute Mobility Among NLS66 and NLSY79 Father-Daughter Pairs

			Father-Daughter Average Age Within:			
	Main Sample	Regression Adjustment	4 Years	3 Years	2 Years	1 Years
1942-1953 Cohorts, Prime Income	0.55	0.52	0.53	0.55	0.56	0.53
(NLS 66)	(0.02)	(0.04)	(0.03)	(0.04)	(0.04)	(0.06)
1957-1964 Cohorts, Prime Income	0.49	0.47	0.47	0.47	0.51	0.42
(NLSY79)	(0.02)	(0.03)	(0.02)	(0.03)	(0.04)	(0.06)
H_0: Measures Equal, p=	0.01	0.32	0.12	0.09	0.4	0.22
Average Age In Years Income Measured						
NLS66 Fathers	50.9	50.9	48.4	48.3	48.1	48.1
NLS66 Daughters	46.2	46.1	47.4	47.8	48.0	48.2
NLSY79 Fathers	47.6	47.5	45.0	44.9	44.9	45.3
NLSY79 Daughters	44.8	44.9	45.0	45.0	45.0	45.3
NLS66 Pairs	694	694	299	225	156	81
NLSY79 Pairs	1334	1334	666	506	311	90

Notes. Estimates show proportion of children in NLS66 and NLSY79 cohorts whose income was higher than that of their parents. The regression adjustment includes separate quartic polynomials in the difference between average father age and average daughter age in the years income is measured. Incomes adjusted to 2015 dollars using CPI for all urban consumers. Robust standard errors in parenthesis.

For Online Publication

Appendix I. Income Distributions (Not for Publication)

This section plots estimated densities of the parent and child income generations in the NLS66 and NLSY79 against comparable estimates from the Current Population Survey's (CPS) Annual Social and Economic Supplement.

In order to make our sample and the CPS samples as comparable as possible, we show distributions of annual income in the years we include in the relevant income measure (in 2015$) for the same birth year cohorts.

We estimate the empirical distributions by calculating the weighted share of observations in the years and birth cohorts corresponding to the correct sample falling below every $1,000 increment between $0 and $1,000,000. We then calculate the density as the change in this share across each increment. The density figures are smoothed using a 6th order local polynomial regression.

Figure A1. NLS66 Parent Generation Income Distribution Density Functions

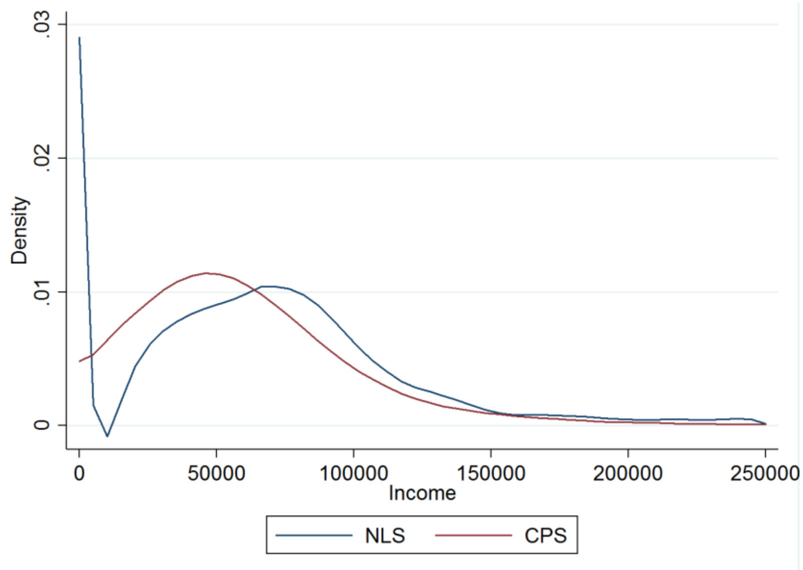


Figure A2. NLS66 Daughters Income Distribution Density Functions

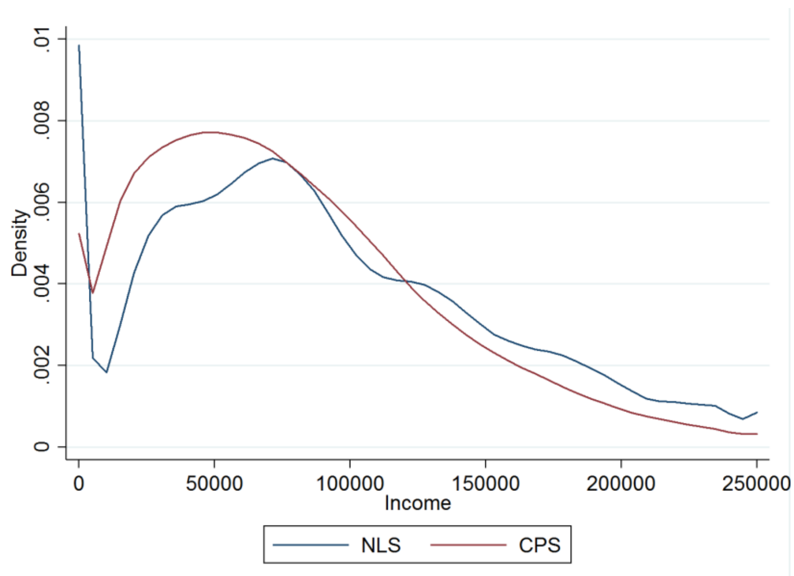


Figure A3. NLSY79 Parent Income Distribution Density Functions

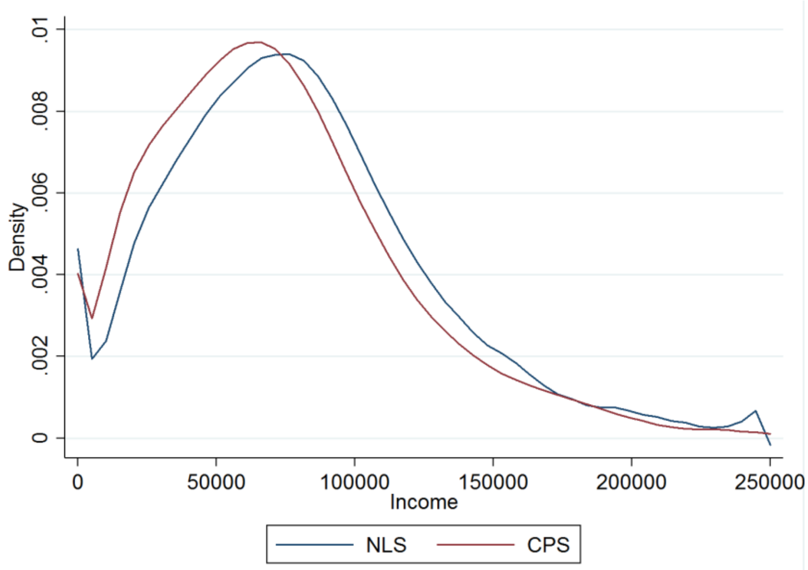
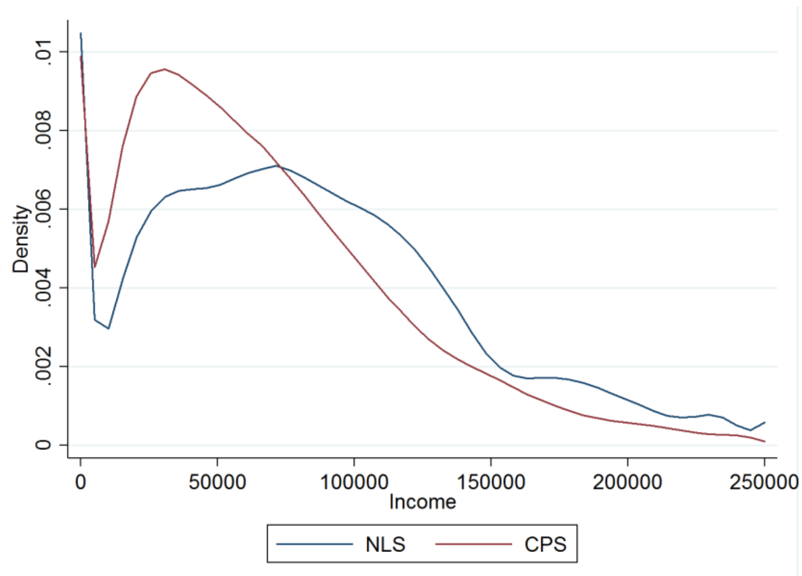


Figure A4. NLSY79 Daughter Income Distribution Density Functions



Appendix II. Re-weighted Income Distributions and Results

This section shows that we are able to replicate the Current Population Survey's (CPS) income distributions by re-weighting our sample. Importantly, this re-weighting does not substantively change our results.

In order to re-weight our sample, we calculate the share of CPS and NLS66/NLSY79 observations falling in to each of 21 income brackets: s_j^{CPS}, s_j^{NLS66}, and s_j^{NLSY79}. The income brackets are $[\$0, \$5{,}000)$, $[\$5{,}000, \$10{,}000)$, ..., $[\$95{,}000, \$100{,}000)$, $[\$100{,}000, \infty)$ where all income is first adjusted to 2015$ using the Bureau of Labor Statistics' Consumer Price Index for urban consumers including all items.

For an observation in income bucket j, we adjust the NLS sampling weight by:

$$w_{ij}^{*} = w_i^{NLS} \times \frac{s_j^{CPS}}{s_j^{NLS}}.$$

The re-weighted income distributions and results using the adjusted weights are shown below.

Figure A5. Re-weighted NLS66 Parent Generation Income Distribution Density Functions

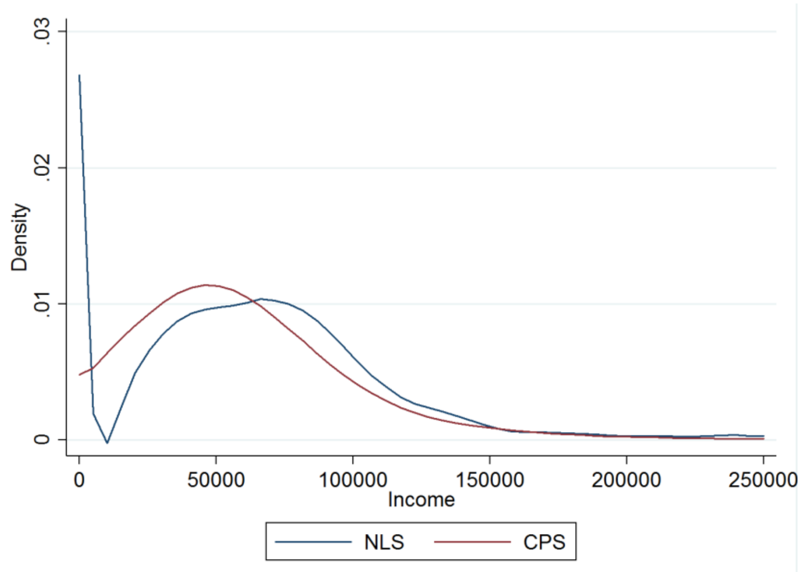


Figure A6. Re-weighted NLS66 Daughter Generation Income Distribution Density Functions

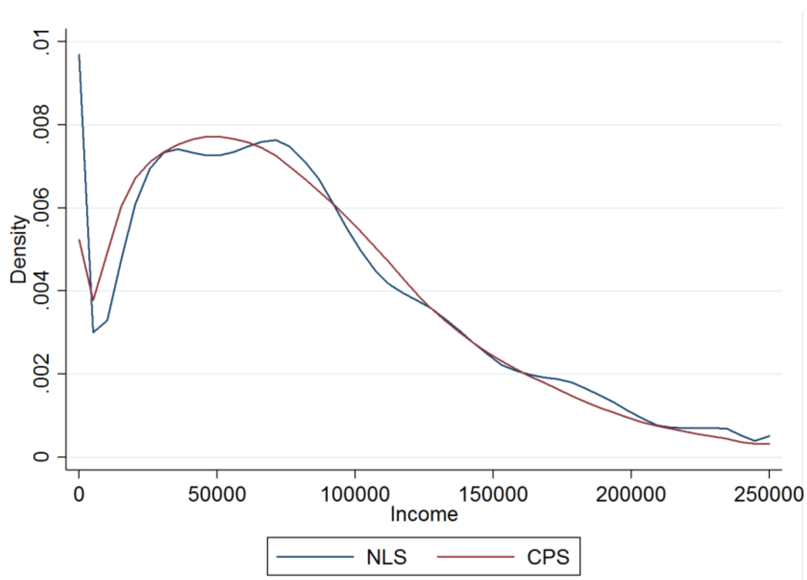


Figure A7. Re-weighted NLSY79 Parent Generation Income Distribution Density Functions

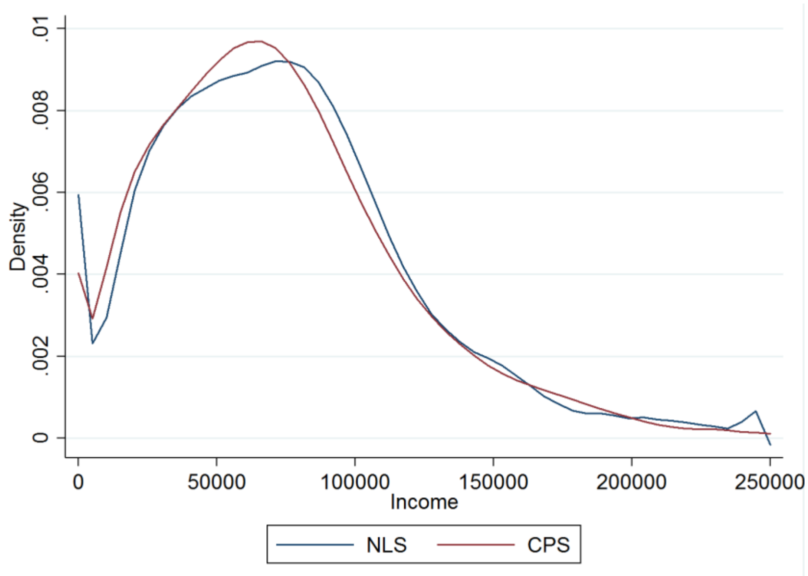


Figure A8. Re-weighted NLSY79 Daughter Generation Income Distribution Density Functions

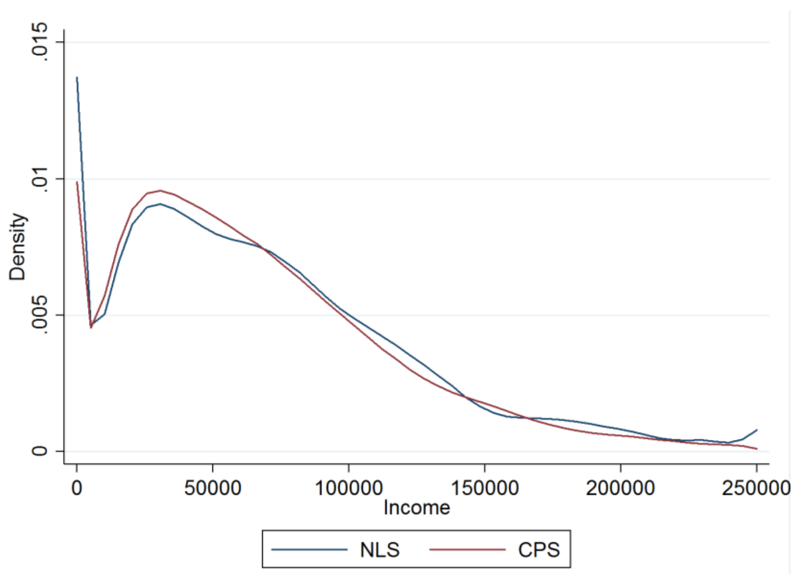


Table A1. Re-Weighted Summary Statistics of NLS66 and NLSY79 Samples

	Mean	SD	Min	Max
A. NLS66 Father-Daughter Pairs (N=694)				
Parent Income Around Age 19 (2015$)	75049	50983	-1460	426097
Adult Income Around Age 48 (2015$)	82855	57785	0	435492
Father Birth Year	1915.47	3.86	1906	1921
Child Birth Year	1948.95	2.83	1942	1953
B. NLSY79 Father-Daughter Pairs (N=1,334)				
Parent Income Around Age 19 (2015$)	75264	45522	-35371	272445
Adult Income Around Age 47 (2015$)	75516	56338	0	334095
Father Birth Year	1931.47	5.37	1920	1942
Child Birth Year	1961.13	2.12	1957	1964
C. NLS66 Father-Son Pairs (N=780)				
Parent Income Around Age 18 (2015$)	76283	47510	2148	426097
Adult Income Around Age 31 (2015$)	66011	36752	0	251121
Father Birth Year	1915.25	3.95	1906	1921
Child Birth Year	1947.85	2.69	1941	1952
D. NLSY79 Father-Son Pairs (N=1,290)				
Parent Income Around Age 18 (2015$)	79020	47197	-44590	272445
Adult Income Around Age 30 (2015$)	60931	35723	0	311539
Father Birth Year	1931.80	5.77	1920	1943
Child Birth Year	1961.26	2.11	1957	1964

Table A2. Re-Weighted Mobility in NLS66 and NLSY79 Father-Daughter and Father-Son Pairs

	Rank-Rank	IGE	Income	Normalized Income
	Panel A. Father-Daughter Pairs			
1942-1953 Cohorts, Prime Income	0.25	0.33	0.29	0.26
(NLS 66)	(0.04)	(0.05)	(0.05)	(0.04)
1957-1964 Cohorts, Prime Income	0.37	0.46	0.41	0.41
(NLSY79)	(0.03)	(0.04)	(0.05)	(0.05)
H_0: Measures Equal, p=	0.02	0.07	0.06	0.02
	Panel B. Father-Son Pairs			
1942-1953 Cohorts, Early Career Income	0.25	0.21	0.25	0.29
(NLS 66)	(0.04)	(0.05)	(0.07)	(0.08)
1957-1964 Cohorts, Early Career Income	0.32	0.32	0.22	0.28
(NLSY79)	(0.03)	(0.04)	(0.03)	(0.04)
H_0: Measures Equal, p=	0.17	0.08	0.71	0.97
1957-1964 Cohorts, Prime Income	0.37	0.41	0.46	0.44
(NLSY79 - Daughter Sampling)	(0.04)	(0.06)	(0.09)	(0.09)

Notes. The NLS66 sample includes 694 father-daughter pairs and 780 father-son pairs. The NLSY79 sample includes 1,334 father-daughter pairs and 1,290 father-son pairs. The Column 2 samples include 672 and 770 father-daughter and father-son pairs from the NLS66, respectively, and 1,317 and 1,268 father-daughter and father-son pairs from the NLSY79, respectively. Incomes measured in 2015 dollars. Robust standard errors in parenthesis.

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