Using Occupation to Measure Intergenerational Mobility

Scholarly investigations of intergenerational mobility typically focus on either the occupations of fathers and sons or their incomes. Using an identical sample of fathers and sons, we examine how estimates of intergenerational mobility in income and occupational prestige are affected by (1) measurement that uses long time averages and (2) varying the point in the life cycle when outcomes are measured. We find that intergenerational occupational mobility is overstated when using a single year of fathers' occupation compared to a 10-year average centered on mid-career. We also find that for both income and occupation, mobility estimates are largest when sons are in their mid-career, suggesting that this may be the ideal period in which to measure their status. Finally, we see differences in the pattern of estimates across the two types of measures: for income, estimates of intergenerational persistence are highest when fathers are in their mid-career; for occupation, estimates are much larger when fathers' occupations are accounted for late in their careers.

Keywords: intergenerational mobility; social mobility; occupational mobility; income; occupation

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As inequality has risen to the forefront of policy discussions in the United States, the discussion has focused not just on the extent to which outcomes, like income, are unequally distributed, but also on the extent to which opportunities to secure those outcomes are unequally distributed. This has in turn spawned a great deal of interest in studies of intergen-

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erational mobility because they are typically motivated by concerns regarding equality of opportunity. The degree to which children's socioeconomic standing in society is determined by their parents' standing in the prior generation may be indicative of the amount of equality of opportunity that exists in society.

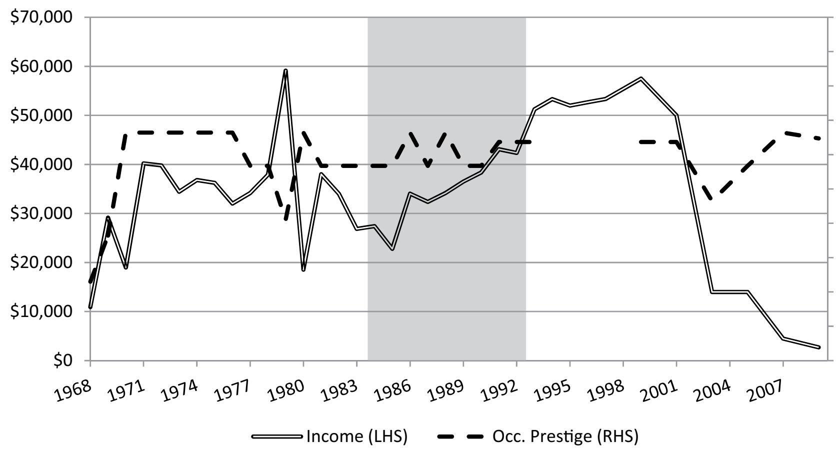
Of course there are many ways to assess intergenerational mobility and many dimensions of socioeconomic status. Sociologists, who pioneered the study of intergenerational mobility, have typically focused on measures of occupation, since occupation conveys important information about social status and is somewhat easier to measure in surveys. Economists, on the other hand, have focused more attention on measures of income. While income has historically been harder to measure, with the advent of panel datasets and opportunities for linking surveys to administrative data sources, economists have made great strides in using income to measure intergenerational mobility. In particular, studies by economists have shown that using larger windows of time over which to measure income, rather than simple snapshots, can have a sizable effect on estimates of intergenerational mobility. This is because income measured over several years better captures the concept of "permanent" or "lifetime" income. For example, Solon (1992) demonstrated that using five-year averages of fathers' income from the Panel Study of Income Dynamics (PSID) leads to substantially lower estimates of the degree of intergenerational mobility than using just a single year of income. Mazumder (2005) shows that even five-year averages may substantially overstate the degree of intergenerational mobility.

The economics literature has also considered how the age at which the income of fathers and sons is measured affects estimates of mobility (Grawe 2006; Haider and Solon 2006). One important finding is that the age at which sons' income is measured can be important because it is sometimes the case that sons who eventually have a high level of income later in life may have an especially low level of income early in their career. This "life cycle bias" can lead estimates of intergenerational mobility to be high when using a sample comprising younger sons. Estimates of intergenerational mobility can also be overstated when using the income of fathers when they are especially young or old. Haider and Solon (2006) show that these biases are minimized when using income measured around age 40 in both generations.

These measurement concerns are important factors to consider when interpreting the recent results from a highly influential study by Chetty et al. (2014) that documents large spatial differences in intergenerational mobility across the United States. Chetty et al. use millions of administrative tax records on parents and children to estimate intergenerational associations in income. Their study is limited in three ways, however: (1) it uses five-year averages (or less) of parent income from 1996 to 2000; (2) many parents in their sample may be past their prime earning years; and (3) children's income is measured using just two-year averages when the children are only around the age of 30.[1]

NOTE: The views expressed here are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Board of Governors of or any other person associated with the Federal Reserve System.

FIGURE 1
Occupational Prestige and Income over Time



NOTE: This chart shows the Nakao-Treas Occupational Prestige Score and real income for person number 117 of the PSID from 1968 to 2009. The years used for the averaging of income and occupation are shaded in gray; during this period, person 117 was between 39 and 47 years old. Over this time period, the PSID surveyed participants annually (beginning with the 1997 wave, surveys were administered biennially). The Nakao-Treas Occupational Prestige Scale was created using the 1989 General Social Survey (GSS) and surveys that asked individuals to rank occupations based on their "prestige"; we attained these data using the University of Minnesota's IPUMS.

An important and largely unexplored question is whether there is an analogous set of concerns regarding measurement when estimating intergenerational occupational mobility. For example, are studies that use occupation measured at just one point in time overstating the degree of intergenerational mobility in "permanent" occupational status? Is it important to take into account when in the life cycle occupation is measured? The answers to these questions should assist in planning and developing a new initiative for monitoring social mobility in the United States.

To illustrate how such issues might matter, consider the concrete case of a father from the PSID (id 117) who was born in 1945 and later completed college. He worked as a construction worker at age 23 in 1968 before becoming a secondary school teacher in 1970. For the remainder of the PSID sample period, his career fluctuated between being a teacher, a counselor, and a school administrator. In Figure 1 we plot this father's income and occupational prestige score between 1968 and 2009. Clearly, his occupational status could depend a great deal on which occupation is used, particularly if we use his occupation when he is young.[2]

The measurement of long-term occupational status may be a more salient issue today than in the past because there have been many dramatic changes in the labor market that could affect how one might understand a single-report measure of occupational status. First, there is evidence of a much higher degree of occupational switching over the life course than in the past (Kambourov and Manovskii 2008). This suggests that the occupation at age 30 may no longer be as good an indicator of social status at age 40. Second, there has also been a notable secular decline in rates of labor force participation (Smith 2011). Therefore, occupation measured at one point in time may be based on a more selected sample than occupation measured over several years. A related point is that the high incarceration rates of black males in recent decades (Western and Pettit 2010) may similarly lead to bias in single-report measures of both occupational mobility and racial differences in occupational mobility.

A separate but somewhat related issue is that there have also been major industrial shifts in the composition of jobs that might affect estimates of intergenerational mobility based on occupation compared to analogous estimates based on income. Such differences may not have been as pronounced in the past. What is most notable is that the secular decline in manufacturing over the past few decades (Charles et al. 2013) could lead measures of occupational status to convey a different signal about socioeconomic status today than it did in the past. Growing evidence shows that job destruction in recent decades has been especially pronounced in occupations in the middle of the skill distribution (Autor and Dorn 2013; Jaimovich and Siu 2012). This so-called polarization of the labor market also may have affected the distribution of skills within occupations and thereby also affected the status of a given occupation. These shifts in the labor market might make it preferable to measure occupational status over a longer period of time. Further, due to these trends, it may be valuable to compare estimates of intergenerational mobility based on occupational status to those using income.

This article attempts to address these concerns, by using longer windows of time to assess "permanent occupational status" of fathers in producing estimates of intergenerational occupational mobility between fathers and sons. Specifically, we use longitudinal data on reported occupation from the PSID. We begin by thinking about the context of intergenerational income mobility where the issues concerning the time horizon of measurement have already been carefully considered. We follow previous studies in the economics literature that use progressively longer-term averages of father's income. We also consider how the *age* at which fathers' and sons' income is measured affects estimates of intergenerational income mobility. With these results on income in hand as a baseline, we then use the *identical sample* to consider whether the father-son intergenerational elasticity in occupational status is similarly affected by using longer time windows. We believe that we are the first U.S. study to compare intergenerational mobility in occupation to intergenerational mobility in income using the same individuals (see Cox, Jackson, and Lu [2009] for a relevant study in Great Britain; also see Bielby, Hauser, and Featherman [1977] for a relevant study on response error).

The results point to several notable conclusions. First, as is the case with intergenerational income mobility, estimates of intergenerational occupational mobility are also overstated when using just a single year of fathers' occupation compared to a 10-year average centered on mid-career. The estimate of intergenerational persistence when using a 10-year average is about 15 to 20 percent higher than the coefficient when using just a single year irrespective of whether we use income or occupational prestige. Second, when we examine how the patterns in intergenerational persistence vary by age, we find that for both income and occupation the estimates are largest when sons are in their mid-career, suggesting that this may be the ideal period in which to measure the status of sons. Third, we see differences in the pattern of estimates across the two types of measures that vary with the age at which father's status is measured. For income, the estimates of intergenerational persistence are highest when fathers are in their mid-career. For occupation, however, estimates are much larger when fathers' occupational status is measured late in their career.

Data and Measurement

The PSID is a large, multigenerational, and nationally representative survey of individuals. The PSID began in 1968 with a sample of more than 18,000 individuals from 5,000 families. The PSID follows the children of the original 1968 sample into adulthood and continues to collect information on those who become household heads, making the study ideal for understanding the dynamics between generations. The survey was annual from 1968 through 1997 and has been biennial since then; variables for occupation and income have been collected in almost every wave of the survey.

Our sample comprises fathers and sons from families that were members of or moved into the original 1968 sample families.[3] Sons are required to have been the male child of a household head at some point in time and also to have become a household head as an adult. Father-son candidate pairs were determined using the PSID's Family Identification Mapping System, which matches children with their parents, grandparents, and great-grandparents.[4] Our restrictions on age and labor market outcomes, which we describe below, limit our examination to the comparison of just two generations.

Income data

We begin by describing our income data and the sample restrictions related to these data. Fathers must have at least 10 years of recorded income and occupation data between the ages 30 and 55.[5] To measure the income of fathers and sons we use total labor income as calculated by the PSID.[6] We convert the income into real terms using the (CPI-U) index (Consumer Price Index for All Urban Consumers) from the Bureau of Labor Statistics (BLS), with 2009 used as the base year. Sons must have at least one year of recorded income between the ages of 37 and 47. Here we are guided by the work of Haider and Solon (2006) and others who show that the age at which sons' income is measured can have pronounced effects on the father-son elasticity in income due to a life cycle bias arising from heterogeneous age earnings profiles. They find that this bias is minimized around age 40.

Occupation data

While measuring income is relatively straightforward, it is somewhat more challenging to decide on the best way to measure occupational status. Although there is general agreement in the literature that occupations should be ranked in some way, there are differing views on the appropriate scale that ought to be used. We considered a number of occupational ranking schemes used by the Integrated Public Use Microdata Series (IPUMS) that fall into two major categories. The first includes those indexes or scores that use the median income or education (or both) of workers in a given occupation to determine a score. Such measures include: Duncan Socioeconomic Index, the Occupational Income Score, the Hauser-Warren Socioeconomic Index, Nam-Powers-Boyd Occupational Status Score, Occupational Education Score, and Occupational Earnings Score. The second category of measures uses survey data from respondents on the perceptions of occupations to construct rankings of occupational prestige. These include the Siegel Prestige Score and the Nakao-Treas Occupational Prestige Score.

The two categories reflect different conceptual approaches to measuring status, and it is not clear to us that one is more correct than the other. We decided to use the Nakao-Treas (1994) Occupational Prestige Score as our main measure. We emphasize a measure based on prestige rather than a measure that was based on income and education. In part, this is because it would make our occupational measure less mechanically related to our income measure and perhaps might better capture other dimensions of social status besides income. A practical advantage of the Nakao-Treas measure is that the timing of when prestige was measured (1989) corresponds reasonably well to the overall time period when occupation is measured in our PSID sample.[7]

Although our main findings use the Nakao-Treas measure of occupational prestige, we also produce estimates using the Duncan Socioeconomic Index, which is roughly a weighted average of the requisite education and income associated with each occupation. For those who prefer this type of measure, its use serves as a robustness check on our results. It should be noted, for the reader new to these methods of occupational ranking, that these scores, whether based on prestige or socioeconomic factors, have been found to be remarkably stable across time and cultures. Furthermore, when surveys are used to determine prestige, as with the Nakao-Treas measure, the occupation, income, and education of the respondent does not significantly influence the responses given; in other words, there is evidence that there exists some ultimate ranking of occupations that is recognized by the general population, regardless of income, education, occupation, or country.

Occupational coding, regardless of which survey is used, can be notoriously difficult due to poor descriptions from respondents or from coding errors by the survey staff. Furthermore, evolving versions of occupation codes make it difficult to compare occupations across time. We overcome some of these problems by using the Retrospective Occupation-Industry Supplemental Data Files, which assigned three-digit 1970 census codes to all 1968–1980 occupation data and synchronized occupation data in the PSID through 2001.[8] Starting with the 2003 data, the PSID switched to the three-digit 2000 census codes. To address the issue of the difficulty in comparing occupations across time, we use the IPUMS generated variable OCC1990, a variable meant to match any census occupation code to the 1990 scheme. While matching census codes from decade to decade will always imply a loss of precision and comparability, this matching scheme, with input from the Census Bureau, the BLS, and IPUMS, is likely the most robust method available.

We measure occupational prestige for individuals between the ages of 30 and 55, who recorded positive income in the same years that they reported occupation. In addition to considering multiyear averages, we also produce estimates where we measure occupation at three distinct points in the life cycle in each generation: early career, mid-career, and late career. An individual's *first occupation* (early career) is the earliest recorded occupation after the age of 30 for which a person was the household head.[9] The *mid-career* is the occupation at age 42, plus or minus five years.[10] The *last occupation* (late career) is determined by using the last recorded occupation before age 55 for which a person was the household head.

To ensure comparability across the various measures of occupational mobility that are considered, our sample is restricted to fathers who had at least 10 years of recorded income and occupation between 1968 and 2009. Their sons must have at least one year of mid-career income and occupation. Given these restrictions, our final sample of 681 father-son pairs includes fathers born between 1921 and 1950 and sons born between 1950 and 1972.

Methodological issues

To determine a person's occupation closest to the age of 42 (the mid-career occupation), we begin by checking for occupation at the age of 42. If no occupation data are recorded in that year, we check for occupation at age 41. If there is still no occupation, we check for occupation at age 43. This algorithm plays out until either a year of recorded occupation is found between 37 and 47, or no recorded occupation is found. In the latter case, this causes a father-son pair to be dropped from our sample. A visual depiction of our algorithm is presented below in Figure 3.

To produce a 10-year average of occupational prestige for an individual, we deploy the same algorithm as above; however, every time an occupation is present, its prestige ranking is added to a running sum, and divided by ten once 10 years have been recorded. This way our 10-year averages are centered on the mid-career of fathers. The 10 years can be taken at any age between 30 and 55, but the averaging centers on age 42. If there are not 10 years of recorded occupation for an individual, that father-son pair is dropped from the sample. Once a father satisfies this condition, then averages of 10-n years are made, for all n in

[1,9] by the same algorithm (stopping each average after 10-n years have been averaged).[11] Ultimately we produce averages of fathers' occupational status or income using anywhere from 1- to 10-year averages centered on the mid-careers of fathers.

Our regressions are all of the following form:

$$S = \alpha + \beta F + \varepsilon,$$

where S represents a measure of either sons' log real income or occupational status and F represents the corresponding measure for the father. The error term is represented by ε, and the equation is estimated by ordinary least squares (OLS). We include a constant term but no other controls so that all factors correlated with the measure of fathers' socioeconomic status are captured by β.[12] When log income is used on both sides of the equation, β can be interpreted as the intergenerational income elasticity and describes the increase in the expected income in the sons' generation in percentage terms associated with a 1 percent increase in fathers' income. Since a higher value of β implies greater persistence in income over generations, a higher value of β also implies lower intergenerational mobility. Indeed, $1 - \beta$ is sometimes used as a measure of the rate of intergenerational mobility.[13]

Summary statistics

In Table 1 we report the summary statistics for the sample. The top half of the table shows the statistics for our main measures for fathers while the bottom half shows the analogous measures for sons. We report the mean occupational prestige (OP) at each stage of the career along with the mean age that corresponds to these measures. We then show the 10-year average of occupational prestige. After that we show the statistics for income measured at each stage of the career.

Results

Income

In Table 2 we show the results for β when we gradually average parent income over more years. Since we use sons' income as close as possible to age 42, we expect our estimates to be relatively immune to life cycle bias. Indeed, even when we use just one year of fathers' income on the right hand side, our estimate is 0.502, which is even higher than Solon's (1992) estimate of 0.413 when using a five-year average of fathers' income. This difference may be explained by life cycle bias as the age of sons in Solon's sample ranged from 25 to 33. As we increase the length of the window of the average of fathers' income around their mid-career, the estimates of the elasticity increase as well. For example, the estimate rises to 0.541 when we use a four-year average, to 0.561 when we use a

TABLE 1
Summary Statistics

Father				
	Mean	*SD*	Min	Max
First Job OP	46.22	13.57	21.4	86.1
First Job Age	35.85	5.16	30.0	46.0
Mid Job OP	47.11	13.22	19.4	86.1
Mid Job Age	42.26	0.84	39.0	46.0
Last Job OP	47.36	13.11	20.7	86.1
Last Job Age	53.69	2.55	39.0	55.0
10-Year Average OP	47.55	12.25	22.3	86.1
First Income	$59,411	$33,155	$3,858	$385,063
First Income Age	35.8	5.2	30.0	46.0
Mid Income	$67,215	$42,406	$2,777	$408,485
Mid Income Age	42.2	0.9	39.0	46.0
Last Income	$66,698	$91,610	$174	$1,824,916
Last Income Age	54.0	2.3	39.0	55.0
Years of Education	12.49	2.91	1.0	17.0

Son				
	Mean	SD	Min	Max
First Job OP	46.86	14.46	20.0	86.1
First Job Age	31.44	2.69	30.0	47.0
Mid Job OP	47.51	14.35	21.4	86.1
Mid Job Age	40.98	1.75	37.0	47.0
Last Job OP	47.32	14.26	16.8	86.1
Last Job Age	46.20	5.68	37.0	55.0
First Income	$49,291	$37,327	$126	$452,500
First Income Age	30.6	1.9	30.0	47.0
Mid Income	$67,009	$68,123	$250	$850,000
Mid Income Age	41.0	1.5	37.0	47.0
Last Income	$76,507	$90,940	$250	$1,000,000
Last Income Age	46.1	5.7	37.0	55.0
Years of Education	13.51	2.36	0.0	17.0
Number of Sons (sample size): 681				
Number of Fathers: 452				

NOTE: Table shows statistics from the PSID sample for the occupational prestige (OP), and income of the first job (First), mid-career job (Mid) and last job (Last), along with the corresponding ages at which these are measured. All prestige measures are Nakao-Treas prestige rankings, using data from the University of Minnesota's IPUMS.

TABLE 2
The Effect of Father's Income on Son's Income Using Multiyear Averages

Years Averaged	β
1	0.502*
	(0.0620)
2	0.513*
	(0.0672)
3	0.528*
	(0.0697)
4	0.541*
	(0.0721)
5	0.543*
	(0.0728)
6	0.558*
	(0.0729)
7	0.561*
	(0.0727)
8	0.575*
	(0.0718)
9	0.574*
	(0.0712)
10	0.583*
	(0.0714)
N = 681	

NOTE: Each entry shows the β from a regression of sons' log income on fathers' log income. Sons' income is measured at an age closest to 42 (with a maximum difference of ±5 years), and fathers' income (2009 dollars) is an average that uses between 1 and 10 years when fathers are between the ages of 30 and 55. Sample is drawn from the PSID. Standard errors are clustered by father and are in parentheses.
$^{*}p < .001$.

seven-year average, and to 0.583 when we use a 10-year average. Mazumder (2005) estimates an elasticity as high as 0.6 when using 16-year averages of fathers' earnings using administrative earnings data. The bottom line is that we do in fact find a significant increase in the estimated intergenerational elasticity (and an implied decline in intergenerational mobility) as we use longer time averages for fathers' income.

In Table 3 we consider how the age at which both sons' and fathers' income is measured affects estimates of the intergenerational income elasticity. We vary the age at which fathers' income is measured across the first three rows and vary the sons' age across the three columns. In the last row we show the results using the 10-year average of fathers' income at each age of the son. Two patterns are

TABLE 3
The Effect of Father's Income on Son's Income Using Various Snapshots in Father/Son Lives

		Son's Income: Age		
		30	42	55
Father's Income: Age	30	0.318*	0.553*	0.500*
		(0.0587)	(0.0730)	(0.0766)
	42	0.301*	0.502*	0.394*
		(0.0519)	(0.0620)	(0.0678)
	55	0.141*	0.220*	0.216*
		(0.0400)	(0.0433)	(0.0454)
	Father: 10 Year Average	0.367*	0.583*	0.502*
		(0.0559)	(0.0714)	(0.0757)
N = 681				

NOTE: Each entry represents the β from a regression of sons' log income on fathers' log income. Income is measured at each of three ages in both generations. For age 30, we use the first year of income at or after age 30, for age 42, we use the age closest to 42 (with a maximum difference of ±5 years), and for age 55, we use income at the age closest to or less than 55. The last row includes a 10-year average of fathers' log income for comparison. Sample is drawn from the PSID. Standard errors are clustered by father and are in parentheses.
*p < .001.

immediately evident. First, looking down the columns and comparing the estimates by the age of the fathers, we find the largest estimates are produced when we use fathers' income measured at age 30. This is somewhat surprising given previous evidence (e.g., Mazumder 2005) of a U-shaped pattern of the transitory variance in earnings that is lowest in the middle of the life cycle. The second consistent pattern is that, when we look across the rows, in all cases the largest estimates are for sons when they are at age 42. The largest estimate, however, is when we use a 10-year average for the fathers around their mid-career and the mid-career income for the sons.

Occupation

In Table 4 we present the estimates where we use longer time averages of occupational status to measure intergenerational mobility. On the left we use the Nakao-Treas occupational prestige measure. We find that when we use just a single year of fathers' occupational prestige the estimate is 0.305. As we progressively average more years of occupational prestige, the estimate rises. For example, when we use a five-year average, the estimate is 0.325. Using an eight-year average, the estimate is 0.347, and using a 10-year average we obtain an estimate of 0.358. At least two points are worth highlighting. First, compared to using log

TABLE 4
The Effect of Father's Occupational Prestige on Son's Occupational Prestige Using Multiyear Averages

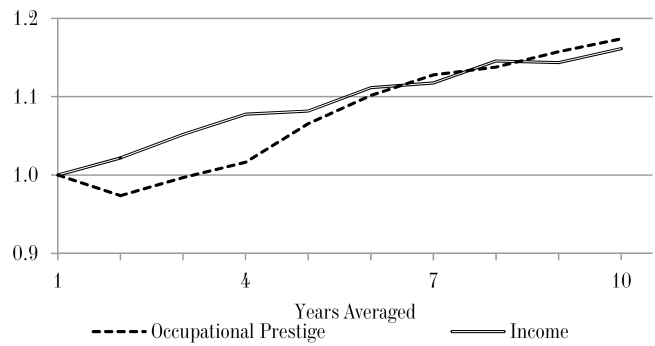
Panel A		*Panel B*	
Nakao-Treas Occupational Prestige		Hauser-Warren Socioeconomic Index	
Years Averaged	β	Years Averaged	β
1	0.305*	1	0.306*
	(0.0437)		(0.0435)
2	0.297*	2	0.309*
	(0.0438)		(0.0434)
3	0.304*	3	0.313*
	(0.045)		(0.0444)
4	0.310*	4	0.315*
	(0.045)		(0.0442)
5	0.325*	5	0.325*
	(0.0452)		(0.0447)
6	0.336*	6	0.334*
	(0.0456)		(0.0448)
7	0.344*	7	0.340*
	(0.046)		(0.0453)
8	0.347*	8	0.341*
	(0.0461)		(0.0453)
9	0.353*	9	0.348*
	(0.0466)		(0.0457)
10	0.358*	10	0.350*
	(0.0468)		(0.0459)
N = 681		N = 681	

NOTE: Each entry shows the β from a regression of sons' occupational status at an age closest to 42 (with a maximum difference of ±5 years) on fathers' occupational status using an average of between 1 and 10 years when the fathers are between the ages of 30 and 55. Panel A uses the Nakao-Treas Occupational Prestige Scale, created using the 1989 General Social Survey (GSS). The Hauser-Warren Socioeconomic Index shown in panel B is a weighted sum of occupational income and education, based on the 1990 U.S. Census and 1989 GSS. The data for both scales are from the University of Minnesota's IPUMS. Sample is drawn from the PSID. Standard errors are clustered by father and are in parentheses.
*$p < .001$.

income where our estimates were between 0.5 and 0.6, the intergenerational coefficient on occupation for the identical sample is much lower at between 0.3 and 0.4. Second, as with income, the estimates appear to rise with time averaging.

On the right of the table, we find very similar results when we use the Hauser-Warren Socioeconomic Index. The estimates rise from 0.31 using just a single

FIGURE 2
Comparing Regression Coefficients of Income and Occupational Prestige



NOTE: The solid line plots the rescaled coefficients from Table 2. The dashed line plots the rescaled coefficients from Table 4. For both series we have rescaled them to an index that equals 1 when using a single year measure of fathers' socioeconomic status. The prestige measures are Nakao-Treas prestige rankings, using data from the University of Minnesota's IPUMS. Sample is drawn from the PSID.

year of fathers' occupation to 0.35 when using a 10-year average. A comparison of the two sets of estimates is also shown in Figure 4.

In Figure 2 we compare how time averaging affects the β we get from using income to the β we get from occupational prestige. Here we rescale the coefficients from Tables 2 and 4 so that using just one year of the measure for fathers is equal to 1. The coefficients on the larger time averages are then all measured relative to using just a single year. We find that while short-term averages appear to have a larger impact on estimates of intergenerational income persistence than on analogous estimates of intergenerational occupational prestige persistence, once we use longer time averages, there is very little difference. In both cases using a 10-year average raises the estimates by 15 percent compared to using just a single year. This suggests that for both dimensions of socioeconomic status using longer time averages appears to produce less downward biased estimates of intergenerational persistence and less upward biased estimates of intergenerational mobility.

We next turn to how the estimates of intergenerational occupational mobility vary over the life cycle of fathers and sons. Here we use only the Nakao-Treas measure of prestige. Similar to the exercise in Table 3, we separately estimate occupational prestige regressions for each combination of ages in each generation, covering the ages of 30, 42, and 55. Starting with the age of the fathers, we find that the largest coefficients are when fathers' occupation is measured at age 55. For example, when sons are aged 42, the coefficients on fathers' occupational prestige gradually increases from 0.294 (when sons are 30 years old) to 0.305 (when sons are 42 years old) and, finally, to 0.358 (when sons are 55 years old). This is the exact opposite of what we found in Table 3, where the

TABLE 5
The Effect of Father's Occupational Prestige on Son's Occupational Prestige Using Various Snapshots in Father/Son Lives

		Son's Prestige: Age		
		30	42	55
Fathers Prestige: Age	30	0.307*	0.294*	0.270*
		(0.0453)	(0.0434)	(0.0431)
	42	0.285*	0.305*	0.272*
		(0.0455)	(0.0437)	(0.0434)
	55	0.339*	0.342*	0.286*
		(0.0440)	(0.0420)	(0.0430)
	Father: 10-Year Average	0.342*	0.358*	0.327*
		(0.0492)	(0.0468)	(0.0464)
N = 681				

NOTE: Each entry shows the β from a regression of sons' occupational status on fathers' occupational status. Occupational status is measured at three ages in both generations. For age 30, we use the first year of occupation at or after age 30; for age 42, we use the age closest to 42 (with a maximum difference of ±5 years); and for age 55, we use occupation at the age closest to or less than 55. The last row includes a 10-year average of fathers' occupational status for comparison. Sample is drawn from the PSID. Standard errors are clustered by father and are in parentheses.
$^*p < .001$.

estimates of the intergenerational income elasticity were always lowest when fathers' occupation was measured at age 55. Indeed the estimates were only in the 0.1 to 0.25 range.

On the other hand, as with the intergenerational income elasticity, the degree of intergenerational occupational prestige persistence is generally highest when measuring sons' occupation in the middle of the life cycle at age 42. This is the case in three of the four rows in Table 5. In all cases, however, using a 10-year average of fathers' occupational mobility yields the largest estimated intergenerational coefficient.

Robustness checks

Our main estimates require fathers to have 10 years of recorded information on occupation between the ages of 30 and 55. There could be some concern that this sample requirement may selectively remove certain types of father-son pairs where fathers have had very low labor force attachment. Therefore, we have relaxed this assumption in Table 6 and have varied the requirement on the number of years of available occupation for fathers. Specifically, we compare the

TABLE 6
The Effect of Father's Occupational Prestige on Son's Occupational Prestige Varying the Maximum Number of Years Averaged

Years Averaged	β_4	β_7	β_{15}
1	0.304*	0.309*	0.309*
	(0.0419)	(0.0420)	(0.0496)
2	0.299*	0.305*	0.297*
	(0.0422)	(0.0421)	(0.0499)
3	0.308*	0.313*	0.308*
	(0.0432)	(0.0432)	(0.0516)
4	0.317*	0.319*	0.315*
	(0.0431)	(0.0432)	(0.0517)
5		0.333*	0.328*
		(0.0433)	(0.0524)
6		0.344*	0.340*
		(0.0436)	(0.0529)
7		0.351*	0.347*
		(0.0441)	(0.0536)
8			0.349*
			(0.0537)
9			0.354*
			(0.0544)
10			0.359*
			(0.0546)
11			0.370*
			(0.0548)
12			0.374*
			(0.0549)
13			0.379*
			(0.0551)
14			0.387*
			(0.0548)
15			0.395*
			(0.0550)
N	745	733	518

NOTE: Each entry shows the β from a regression of sons' occupational prestige at an age closest to 42 (with a maximum difference of ±5 years) on fathers' occupational status using an average of either 4, 7, or 15 years when the fathers are between the ages of 30 and 55. The sample in each column requires either 4, 7, or 15 years of available data on fathers' occupation. Samples are drawn from the PSID. Standard errors are clustered by father and are in parentheses.
*$p < .001$.

FIGURE 3
"Age Closest to" Algorithm

Main Algorithm: Favors Younger Ages

AGE	37	38	39	40	41	42	43	44	45	46	47
PRESTIGE	50	50	n/a	**52**	n/a	n/a	n/a	60	60	62	62
ORDER				STOP	2	START	3				

Alternative Algorithm: Favors Older Ages

AGE	37	38	39	40	41	42	43	44	45	46	47
PRESTIGE	50	50	n/a	52	n/a	n/a	n/a	**60**	60	62	62
ORDER					3	START	2	STOP			

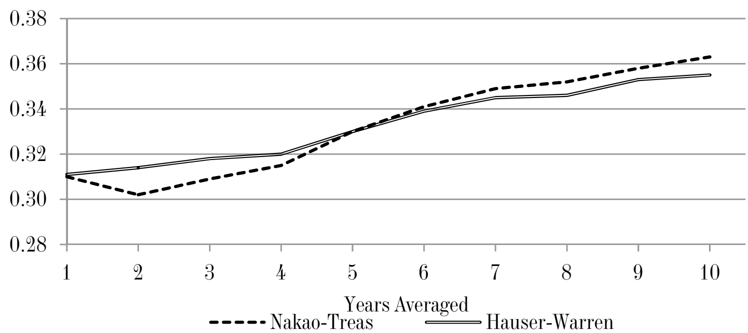
NOTE: The first graphic shows our main algorithm for how we determine a person's occupation closest to the age of 42, which we call "middle age." We also use this approach to construct multiyear averages of fathers' socioeconomic status. The algorithm is described in detail in the text. Alternatively, we can run the algorithm in reverse, as shown in the second graphic. This alternative favors occupations recorded at older ages. As the example shows, for the same individual, the second algorithm returns the person's occupation at age 44. This is in contrast to the first algorithm, which chose occupation at age 40.

estimates for when the required number of years of data over the age range of 30 to 55 is either four, seven, or 15 years.

Our sample size when requiring just four years of data on occupation rises to 745. In contrast, when we restrict our sample further by requiring 15 years of data on occupation, our sample falls to 518. Nevertheless, our estimates are remarkably similar in all cases where we can use a common time average. For example, intergenerational persistence in occupational prestige is rounded to 0.32 in all three cases when we use a four-year average of fathers' occupation in all three samples. Using a 15-year average of fathers' occupational prestige yields an estimate of 0.395. This suggests that the intergenerational persistence in occupational prestige is probably close to 0.4.

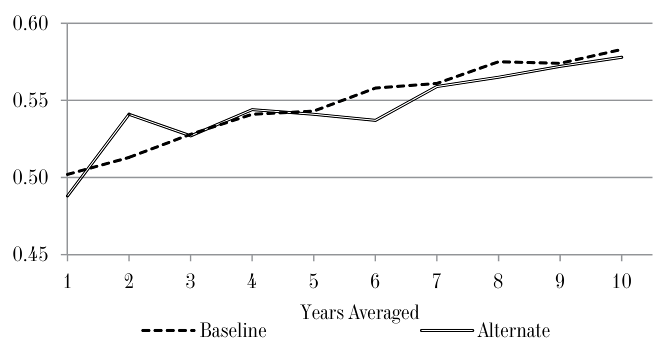
Earlier we described our algorithm for calculating the multiyear averages centered on the mid-career of fathers (which is depicted visually in Figure 3). When income or occupation is missing at a particular age, there is an arbitrariness about what direction we should go (lower or higher age) to find a nonmissing value. In our main algorithm, if data are missing at age 42, we begin by looking for data at age 41 rather than 43. The alternative algorithm is also shown in Figure 3. The main algorithm is more likely to measure socioeconomic status at a younger age than the alternative algorithm. To check how this might alter our estimates we reran the regressions from Tables 2 and 4, using the alternative method for constructing multiyear averages. This is shown in Table 7. In Figure 5 we compare the estimates for the intergenerational income elasticity. Overall we see very little difference in the results using this alternative approach.

FIGURE 4
Comparing Occupational Ranking Scales



NOTE: Figure shows plots of the coefficients described in Table 2.

FIGURE 5
Comparing Averaging Algorithms



NOTE: Figure shows plots of the coefficients described in Tables 2 and 7.

Conclusion

Parallel literatures in economics and sociology have estimated rates of intergenerational mobility using different measures. Economists have largely focused on income mobility and have considered how using only a snapshot of income at a point in time can lead to attenuation bias in the intergenerational income elasticity, leading researchers to potentially overstate intergenerational mobility. This can also be further exacerbated by life cycle bias. For example, the intergenerational elasticity is typically lower when using the income of sons when they are relatively early in their career. The economics literature has emphasized the use of longer-term time averages and ideally measuring income in mid-career. A major open question is whether estimates of intergenerational mobility in occu-

TABLE 7
Results of Alternative Averaging Algorithm Using Income and Occupational Prestige

Occupational Prestige (Nakao-Treas)		Log Real Income	
Years Averaged	β	Years Averaged	β
1	0.305* (0.0439)	1	0.488* (0.0616)
2	0.307* (0.0454)	2	0.541* (0.0718)
3	0.305* (0.0450)	3	0.527* (0.0684)
4	0.320* (0.0455)	4	0.544* (0.0699)
5	0.327* (0.0453)	5	0.541* (0.0723)
6	0.335* (0.0458)	6	0.537* (0.0721)
7	0.344* (0.0460)	7	0.559* (0.0729)
8	0.349* (0.0464)	8	0.565* (0.0714)
9	0.354* (0.0466)	9	0.572* (0.0710)
10	0.363* (0.0469)	10	0.578* (0.0708)
N = 681		N = 681	

NOTE: See the notes for Tables 2 and 4. The entries are similar to those in Tables 2 and 4 but use an alternative averaging algorithm as described in the text. Standard errors are in parentheses.
* $p < .001$.

pational status are similarly impacted by these measurement issues.

In this article we construct an intergenerational sample from the PSID where we observe both occupation and income for the same individuals over the same time periods and at the same ages. We find that, as with the literature on intergenerational income mobility, estimates of intergenerational occupational persistence are also attenuated when using just a single year of occupation compared to a 10-year average. The coefficient when using a 10-year average of fathers' socioeconomic status centered on the age of 42 is about 15 to 20 percent higher than the coefficient when using just a single year irrespective of whether we use income or occupational prestige.

When we examine the patterns in the intergenerational coefficients by age we find that, for both income and occupation, the attenuation bias is lowest when sons are in their mid-career. However, there are notable differences in estimates of income mobility versus occupational mobility depending on the age at which fathers' status is measured. For income, the highest estimates of intergenerational income persistence occur when fathers are in their early career. For occupation, in contrast, the highest estimates are found when fathers are in their late career.

Future research may build on these descriptive findings to better understand the sources of these patterns, particularly with respect to occupation, where we know less about the dynamics of occupational prestige over the course of the career. It may be useful for other studies to replicate these patterns in other datasets and in other settings. We also hope that these findings will assist the ongoing initiative to develop a new infrastructure for monitoring mobility in the United States.

Notes

1. There are also potential measurement issues related to income that are missing in their data prior to 1999 for nonfilers. The extent of the bias in their estimates from their data limitations may not be fully resolved until similar types of administrative records covering the entire life cycle for two generations become available.

2. For example, the Nakao-Treas index of occupational prestige would assign a value of around 66 to a secondary school teacher but only 34 to a drywall installer.

3. We use only the nationally representative portion of the original sample and exclude both the "Latino" sample and "Immigrant sample" that were added in later years.

4. Fathers can be either biological (98 percent of our sample) or adoptive (2 percent).

5. The restriction on the fathers' age at which income is measured also reduces bias arising from greater transitory variance in income among fathers when they are especially young or old (Mazumder 2005).

6. From 1968 through 1992, the PSID specified "total labor income" (TLI), which included wages and salary, bonuses, overtime, tips, commission, "other labor income," professional practice/trade, and amount from extra jobs. From 1993 forward, the PSID's TLI variable either includes or subtracts different components of labor income. We make minor modifications to the variables after 1993 to make the measure more consistent. Furthermore, to avoid introducing measurement error from imputations, any data that the PSID listed as having "major assignments" or "minor assignments" were not included.

7. The year 1989 is near the midpoint of the census occupational classification schemes (1970, 2000) used by the PSID. Nakao-Treas utilizes the 1980 occupational classification scheme.

8. The PSID originally coded occupation in very broad one- or two-digit codes from 1968 to 1980. While the release of the retrospective files is useful in that it allows for a more granular view of occupations throughout the entirety of the PSID's tenure, it also introduces inconsistent sampling/coding error across time. As Kambourov and Manovskii (2008) explain, because the 1999 re-coders had access to an individual's occupation records in multiple years, they were able to smooth year-to-year discrepancies in reporting. Put differently, because the interviewing PSID staff member in 1981 did not have access to an individual's prior year occupation code, it is possible that a slight difference in description or interpretation of the individual's job could be recorded as a different occupation code than the prior year, even if that individual had not changed occupations. So while the data from 1968 to 1980 suffer less from this error, the data from 1981 on are still subject to this flaw, which introduces varying levels of error with a definitive discontinuity between 1980 and 1981. Despite these difficulties, access to the retrospective files is beneficial because it allows for more consistent occupation comparisons across time.

9. The PSID did ask in certain years for an individual's "first job," but there is no information taken that provides more detail on the circumstances of employment. We do not know, for example, whether this was a respondent's part-time job in eighth grade or a first postcollege position. To ensure that we capture

each individual at a similar, but early, point in life, we rely on our own definition of "first job."

10. We use age 42 since it lies roughly halfway between age 30 and 55.

11. Our algorithm, which moves from age 42 to younger ages (if no data are available at age 42), favors the creation of multiyear averages at younger ages compared to an algorithm that searches older ages first. We show later that our results are insensitive to the "direction" our algorithm moves.

12. Typically researchers use a limited number of controls since the intergenerational parameter is generally given a descriptive rather than a causal interpretation. We do not include age controls since this article is very focused on measuring socioeconomic status at particular ages.

13. One interpretation of $1 - \beta$ is that it describes the approximate rate at which income differences between families in percentage terms are eliminated over a generation.

References

Autor, David H., and David Dorn. 2013. The growth of low-skill service jobs and the polarization of the U.S. labor market. *American Economic Review* 103 (5): 1553–97.

Bielby, William T., Robert M. Hauser, and David L. Featherman. 1977. Response errors of nonblack males in models of the stratification process. *Journal of the American Statistical Association* 72 (December): 723–35.

Charles, Kerwin Kofi, Erik Hurst, and Matthew J. Notowidigdo. 2013. Manufacturing decline, housing booms, and non-employment. NBER Working Paper No. 18949, Cambridge, MA.

Chetty, Raj, Nathaniel Hendren, Patrick Kline, and Emmanuel Saez. 2014. Where is the land of opportunity? The geography of intergenerational mobility in the United States. NBER Working Paper 19843, Cambridge, MA.

Cox, D. R., Michelle Jackson, and Shiwei Lu. 2009. On square ordinal contingency tables: A comparison of social class and income mobility for the same individuals. *Journal of the Royal Statistical Society, Series A (Statistics in Society)* 172 (2): 483–93.

Grawe, Nathan D. 2006. Lifecycle bias in estimates of intergenerational earnings persistence. *Labour Economics* 13 (5): 551–70.

Haider, Steven, and Gary Solon 2006. Life-cycle variation in the association between current and lifetime earnings. *American Economic Review* 96 (4): 1308–20.

Jaimovich, Nir, and Henry E. Siu. 2012. The trend is the cycle: Job polarization and the jobless recoveries. NBER Working Paper No. 18334, Cambridge, MA.

Kambourov, Gueorgui, and Iourii Manovskii. 2008. Rising occupational and industry mobility in the United States: 1968–97. *International Economic Review* 49 (1): 41–79.

Mazumder, Bhashkar. 2005. Fortunate sons: New estimates of intergenerational mobility in the U.S. using Social Security earnings data. *Review of Economics and Statistics* 87 (2): 235–55.

Nakao, Keiko, and Judith Treas. 1994. Updating occupational prestige and socioeconomic scores: How the new measures measure up. *Sociological Methodology* 24:1–72.

Smith, Christopher L. 2011. Polarization, immigration, education: What's behind the dramatic decline in youth employment? Federal Reserve Board Finance and Economics Discussion Series, Washington, DC.

Solon, Gary. 1992. Intergenerational mobility in the United States. *American Economic Review* 82 (3): 393–408.

Western, Bruce, and Becky Pettit. 2010. Incarceration and social inequality. *Dædalus* 139 (3): 8–19.