NBER WORKING PAPER SERIES

INTERGENERATIONAL MOBILITY IN EDUCATION: VARIATION IN GEOGRAPHY AND TIME

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Working Paper 25324
http://www.nber.org/papers/w25324

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
December 2018

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NBER Working Paper No. 25324
December 2018
JEL No. I2,I21,I24,J24,J48

ABSTRACT

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December 8, 2018

Abstract

Although the measurement of intergenerational income mobility has seen a rapid increase in attention and policy discussions, similar examinations of educational mobility in the U.S. are lacking. This paper begins to fill this gap by documenting differences in educational mobility across time (1982-2004) and geography (U.S. states). The study complements recent estimates of intergenerational income mobility because educational mobility both contributes to income mobility and is a target for education policies. We both develop a method to compute intergenerational correlation coefficients which respects the unique properties of education attainment, as well as utilize standard measures in the literature. While naive intergenerational regressions of years attained suggest a slight increase in mobility over the sample period, we find that mobility fluctuated: decreasing over roughly the first decade and increasing in the second. In addition, there is also substantial geographic variation in education mobility. We identify local community and policy factors, such as the existence of high school exit exams, that are correlated with educational mobility as well as a lack of increase in mobility in the South.

1 Introduction

The purpose of this paper is to document patterns in the intergenerational correlation of educational attainment. While prominent recent work (Chetty et al. (2014a) and Chetty et al. (2014b)) has focused on intergenerational correlations in income, less work has focused on education as the variable of interest. Building on previous work, we analyze patterns in education mobility, across both time and geographical regions in the contemporary U.S. In addition to standard approaches, we develop a simple method for estimating mobility in education that recognizes the possibility of changing education standards over time.

While the topic of income mobility has been well studied, we believe the study of education mobility offers distinct insights. Since education contributes significantly to lifetime income, one reason for studying educational mobility is to assess the degree to which it explains variation in income mobility. In turn, the study of education mobility could also yield information on the effectiveness of educational policies in addressing issues of income mobility. At the same time, there may be differences between education and income mobility. Since education attains its terminal value relatively early in the life cycle, and is more directly influenced by parents, it serves as a measure of early life opportunities available to the child. In comparison, income depends on a wide variety of intervening factors that may come into effect later in life (e.g. career choice or the Great Recession). Hence, measures of education mobility may be of more interest when studying early life opportunities or the concept of ”equality of opportunity”. Finally, measuring education mobility is easier than income mobility because terminal values of education attainment are relatively easy to obtain in data. In contrast, measurement of income is often troubled by the issue of disentangling permanent income from transitory income shocks. By focusing on education, the set of feasible data becomes significantly larger.

In this paper, we focus on producing estimates of intergenerational mobility in education that respect the way in which educational attainment is measured. By nature, our variable of interest requires slightly different methods from those used to study income. Measurements of educational attainment are typically discrete and sparse. While it is relatively safe to assume that income is continuously distributed, the observed patterns in educational attainment do not support this assumption. In response to the issue of discreteness, one solution is to use a natural parameterization of education: the years of education attained. While this method gives results that are easily interpreted, it has a shortcoming: changes in the marginal distribution of education may result in changes to the estimated mobility coefficients. For example, comparing two cohorts of children, it is likely that children from the later cohort have a higher rate of college graduation.[1] In our view, this change in the fraction of children attending college should not necessarily have affect the mobility coefficient: it is important to consider the education level of their parents as well. If the increased fraction of children graduating college comes from the top of the parental education spectrum, we do not view this as a real increase in mobility.

We proceed by assuming that measured educational attainment is a discrete, ordinal categorization of an underlying continuous variable, which we refer to as human capital for the sake of discussion. We seek to estimate mobility in this latent, continuous variable. When only discrete education is observed, the main difficulty lies in differentiating changes in mobility from changes in the marginal distribution of education. It may be argued that education mobility measures should depend on these marginal distribution changes. The resolution of this issue depends on the concept of mobility that the researcher wants to capture. For comparability with recent studies of income mobility, we focus on the concept of relative mobility: the dependence of a child’s position in the education distribution of his/her generation, on the position of the parent.

Relative mobility is distinct from absolute mobility, which focuses on whether children are doing better than their parents on a particular invariant scale (e.g. years of education completed). Both concepts of economic mobility are relevant in addressing different policy concerns. For example, when assessing improvement in education outcomes over time, absolute mobility is the appropriate measure. On the other hand, when studying the intergenerational

[1] This hypothesis is supported by the data: we present supporting findings later in the paper. Additionally, the same trend holds true, albeit to a lesser degree, for the parents of these children as well.

origins of social stratification or "equality of opportunity" among peers of the same cohort, relative mobility becomes the relevant concept. It is important to develop separate measures for relative and absolute mobility because they could exhibit very different patterns (Breen and Jonsson, 2005). At the national level, Winship (2014) finds substantial differences between absolute and relative mobility, for a child cohort born in the 1970s.[2] Our objective is to measure relative mobility and examine its trends and geographic distribution fo a recent set of birth cohorts in the U.S.

We develop two specifications for estimating relative mobility in education. Similar to rank-rank regressions, each of our methods imposes assumptions on the latent variable so that the distribution is known. In the first specification, we impute the mean percentile of the latent variable for each education level.[3] This specification assumes that the intergenerational transmission of education percentiles is linear: we verify that this assumption is not contradicted by the data. We also develop an alternative specification based on the assumption that this latent variable is normally distributed.

We apply our method to three separate representative surveys of high schoolers in the United States. Conducted by the National Center for Education Statistics (NCES), these three surveys span a period of roughly 2 decades. Hence, they provide three snapshots of national trends in education mobility. Furthermore, these surveys also sampled a wide range of geographical areas, permitting some comparison across U.S. states and regions as well. Our results suggest that education mobility has increased for recent cohorts in the U.S. We find some evidence that the measure of education matters in documenting these recent trends due to changes in the distribution of educational attainment. Turning to geographic variation, between states, a number of contextual and policy measures - including the presence of high school exit examinations - are associated with lower education mobility. This finding is expected, and verifies that our mobility findings lead to sensible patterns. Furthermore, we find some correlation between our measures of education mobility and income mobility measures from Chetty et al. (2014b), as well as evidence of region variation, with the South lacking recent increases in mobility.

1.1 Existing Literature

There is substantial interest in estimating intergenerational mobility for variables other than income. One body of existing research effectiveness of educational policies in remediating issues of social mobility (Blanden and Machin,

[2]He finds that relative mobility appears to be limited, while absolute mobility is high. The discrepancy arises from increasing living standards across generations, such that children tend to fare better than their parents. However, the same child still has a low chance of escaping a situation of *relative* disadvantage.

[3]Our method is very similar to a study by Goldring et al. (2015). In that study, as in ours, education is taken to be a discrete categorization of an underlying continuous variable (which they term SES). However, in contrast to our study, the dependent variable in that paper is mortality, which is a binary variable. While we could replicate their approach by choosing a binary outcome (e.g. child's high school graduation), we choose, in our main analysis, to look at changes along the entire support of child/parental education.

2004; Heineck and Riphahn, 2009).[4] In line with these prior studies, our study can provide descriptive evidence about the associations between mobility and high school exit exam policies. Since we have variation in policies across states and time, it is possible to group states by the presence of such policies, and determine if these policies affected educational mobility.

Besides those mentioned above, there are a few existing studies that focus on intergenerational mobility in education. Chevalier et al. (2003) and Hertz et al. (2007) both compare educational mobility across countries.[5] The former study focuses on the relationship between mobility and inequality across countries, while the latter estimates income and education persistence separately. Both of these studies do not examine the U.S. at a sub-national level. In addition, these prior studies use either years-on-years regressions or eigenvalue measures of mobility. We will argue that our estimates are better suited to the measurement of relative mobility. In addition, Azam and Bhatt (2015) measures intergenerational mobility in education in India: similar to this paper, they are concerned with measuring changes in relative mobility. They achieve this through standardizing years attained within each cohort, which is an alternative approach that we also explore.

With reference to the U.S., Hilger (2017) measures intergenerational mobility in education, from the 1940s onwards. In comparison to his sample, ours does not reach as far back, historically; however, taking advantage of the sampling of our data, we are able to estimate mobility figures for smaller geographic units - census MSAs - and do not need to make assumptions about links between co-residence with parents and educational attainment.[6] In addition, Nguyen et al. (2005) examines educational mobility in a single cross section of U.S. children, but does not examine geographical variation. Internationally, Blanden et al. (2005) study intergenerational correlations in both income and education for two cohorts of children in the U.K. For their sample (1958 to 1970), they find that child education has become more sensitive to parental income and education. They also find that the correlation between parental income and child education forms a significant part of the estimated intergenerational correlations in income (about a third of the total magnitude).

[4]In comparison to other determinants of income (e.g. cognitive ability), one motivation for studying educational mobility in specific is the prevalence of policies that directly influence educational mobility. The studies cited do not examine the U.S.: Blanden and Machin (2004) consider the effect of expansion policies for higher education in the U.K., while Heineck and Riphahn (2009) studies a change in the German education system. Chevalier et al. (2003) also cite policy relevance as a reason for studying educational mobility. In addition, they also cite the relative difficulty of measuring lifetime income.

[5]See Black and Devereux (2011) for a survey of current research literature on intergenerational mobility, which includes the two cited sources.

[6]Since Hilger uses cross-sectional Decennial Census data, he is only able to examine intergenerational correlations between parents and children if the children are residing with the parents during the data collection. The necessary assumption that Hilger provides evidence for is that children who live with their parents after completing schooling have representative mobility profiles as children who do not.

2 An Empirical Model of Mobility in Education

In our model, parents transmit human capital to their children. Human capital is a summary measure of resources, norms, and ability, which contributes to educational attainment. Indexing families by i and generations by $g \in \{0, 1\}$, we assume a linear transmission of human capital, as in (1).[7] The important coefficient in this model is $\alpha_{1,r,t}$, which can vary across geographic regions r and time periods t.

$$h_{i,1} = \alpha_{0,r,t} + \alpha_{1,r,t} h_{i,0} + \epsilon_i \tag{1}$$

Parental income has been deliberately omitted from the model: we wish to include parental income as a channel for intergenerational transmission of educational attainment. In other words, if highly-educated parents are more able to fund higher education for their children, we want to capture that effect in our estimate.

Education is assumed to be a discrete categorization of human capital. In other words, education and human capital are almost equivalent, but educational attainment involves some information loss. Education is constant for all values of human capital between certain thresholds (2). The numerical values v for these categories could describe, for example, the years of education attained.

$$e_i = \begin{cases} v_1 & h_i \in [\delta_{0,t} = \delta_{min}, \delta_{1,t}] \\ v_2 & h_i \in (\delta_{1,t}, \delta_{2,t}] \\ & \vdots \\ v_M & h_i \in (\delta_{M-1,t}, \delta_{M,t} = \delta_{max}] \end{cases} \tag{2}$$

The thresholds δ_{mt} can be interpreted as education standards, determining the minimal human capital needed to receive a , which may vary across time periods, due to changes in norms, incentives, and costs of education. For example, compulsory education laws might eliminate the lowest category of e_i. For this reason, in our empirical work we allow these thresholds to vary freely across time periods as well.[8]

The discrete categorization of human capital as education affects both the dependent variable (child human capital) and the key regressor (parent human capital). The discrete nature of the dependent variable can be addressed using standard regression methods for ordinal data: for example, suppose that parental human capital were fully observed,

[7](1) can be viewed as the reduced form of a simple human capital investment model, similar to Solon (2004). See Section A for a detailed description.

[8]These thresholds could vary across geographical regions (states or cities) as well. In our analysis of national trends, we accommodate a limited form of such variation, through the inclusion of state-year fixed effects. Section 2.3 contains a more detailed discussion.

but child human capital only up to the level of education. In this case, an ordered probit regression could be used to estimate relative mobility. On the other hand, the discrete nature of parental human capital is more problematic. In the model, even if the transmission of human capital is linear, the transmission of educational attainment is likely to be nonlinear. For simplicity, consider the case in which child human capital is fully observed, but parental education takes one of M education levels (3).

$$h_{i,1} = \sum_{m=1}^{M} \beta_m \mathbf{1}\left(e_{i,0} = v_m\right) + \nu_i \tag{3}$$

Equation (3) describes the model-derived causal relationship between parental education and child human capital. This equation cannot, in general, be meaningfully reduced to a linear regression in $e_{i,0}$. The exception would be the unlikely case that $(\beta_m - \beta_{m'})/(v_m - v_m')$ were constant for all m, m'.

In this paper, our empirical objective is to recover coefficient α_1 in (1) (subscripts r and t have been suppressed), and to compare this coefficient across geographic regions and time periods. We denote by Δ_m the difference in expected human capital between education level v_m and the lowest level:

$$\Delta_m \equiv \mathbb{E}\left[h_{i,0} \,|\, h_{i,0} \in (\delta_{m-1,0}, \delta_{m,0}]\right] - \mathbb{E}\left[h_{i,0} \,|\, h_{i,0} \in (\delta_{min}, \delta_{1,0}]\right]$$

The coefficients on parental education from (3) are related to α_1 as follows:

$$\mathbb{E}\left[\hat{\beta}_m\right] - \mathbb{E}\left[\hat{\beta}_1\right] = \alpha_1 \Delta_m \tag{4}$$

As (4) shows, the coefficients on parental education are not straightforward indicators of relative mobility: they are also affected by the process of discretization. That is, for a particular level of parental education, the estimated regression coefficient is the product of the intergenerational correlation coefficient and the conditional expectation of human capital for parents with that level of educational attainment. Furthermore, a linear regression in years of parental education is only interpretable when all the Δ_m's are identical. This assumption would impose that going from 10 to 11 years of schooling represents the same increase in human capital as going from 11 to 12 years.

One potential response to this issue is to discount the information contained in the values of education categories and to simply estimate (3) with indicator variables for each ordinal level of education. The drawback to this approach is the difficulty in assessing changes in mobility. Any comparison of mobility across two time periods or two locations requires a comparison between two sets of M coefficients each. Because of this practical difficulty, we do not use this approach in our primary analysis.

At the same time, (4) suggests a method of re-weighting in order to compare coefficients across geographical regions (or, equivalently, time periods). Consider two regions, c and d. In order to compare the underlying mobility coefficient $\alpha_{1,c}$ and $\alpha_{1,d}$:

$$\left(\mathbb{E}\left[\hat{\beta}_{m,c}\right] - \mathbb{E}\left[\hat{\beta}_{1,c}\right]\right)\Delta_{m,c}^{-1} - \left(\mathbb{E}\left[\hat{\beta}_{m,d}\right] - \mathbb{E}\left[\hat{\beta}_{1,d}\right]\right)\Delta_{m,d}^{-1} = \alpha_{1,c} - \alpha_{1,d} \tag{5}$$

Because the latent distribution of parent's human capital is unobserved, it is not possible to estimate $\Delta_{m,c}$ in general. Hence, we next impose some distributional assumptions of unobserved human capital, so that $\Delta_{m,c}$ can be recovered from observed information. [9]

2.1 Recovering Intergenerational Correlations Using Education Percentiles

As discussed previously, in order to recover the intergenerational correlation in unobserved human capital, some distributional assumptions must be made. In this paper, we explore two alternative assumptions. The first assumption is that human capital percentiles are linearly transmitted: in other words, the position of the child in his/her marginal distribution of human capital depends on the parent's position in their respective marginal distribution. Since the percentiles of human capital must be uniformly distributed between 0 and 1, this assumption allows us to calculate the expected percentile of human capital, conditional on the observed level of education. As shown in (6), the conditional expectation Δ_m can be recovered from probability measures corresponding to observed frequencies in the data. Essentially, for each parent, the *education percentile* or *percentile mean* is assigned as the fraction of parents with strictly less education, plus one-half the fraction of parents with equal education.

By this assumption, the conditional expectation of education percentiles can be expressed in terms of the empirical distribution function for educational attainment:

$$\Delta_m = Pr(e_{i,0} < v_m) + \frac{Pr(e_{i,0} = v_m)}{2} - Pr(e_{i,0} = v_1) \tag{6}$$

2.2 Recovering Intergenerational Correlation under Normality Assumptions

As an alternative approach to education percentiles, we instead assume that latent human capital is normally distributed. Under this assumption, expected human capital, conditional on an observed education level, can be derived from an alternative formula, based on the truncated normal distribution.[10] For notational simplicity, let $F(v)$ denote the

[9] Appendix B illustrates the model using a simple numerical example. In Appendix C, we also compare our methods other alternative measures of mobility: ordinal variable regressions and matrix-based measures of mobility.

[10] We standardize latent human capital to be mean 0, standard deviation 1, which is trivial under the assumption that it is normally distributed.

empirical distribution function of parental education, i.e. the fraction of observed parents with education no greater than v. Then, under these alternative assumptions, Δ_m is given by (7), where Φ (resp. ϕ) denotes the distribution function (resp. probability distribution function) for the standard normal distribution. As an alternative to education percentiles, we also calculate human capital using this method, which we term *truncated normal expectations*.

$$\Delta_m = \frac{\phi\left(\Phi^{-1}\left(F(v_{m-1})\right)\right) - \phi\left(\Phi^{-1}\left(F(v_m)\right)\right)}{F(v_m) - F(v_{m-1})} \tag{7}$$

2.3 Comparing Intergenerational Correlations Across Time and Geography

By design, both methods of calculating human capital are invariant to changes in the marginal distribution of educational attainment. In an intergenerational regression of human capital measures, the coefficient on parent's human capital describes how the child's position in his/her education distribution depends on the parent's position. Our approach is similar to rank-rank regressions: which have been widely used in recent research to measure relative mobility in income (Chetty et al. (2014a), Chetty et al. (2014b)). Our method simply adapts the concept of a rank-rank regression to suit discrete data. Similar to rank-rank regressions, the key assumption is that the human capital measure is linearly transmitted from parent to child.

Using simulated data, we test both of our methods against commonly-used intergenerational regression methods.[11] When applied to simulated human capital data, our chosen methods perform better: they stay relatively constant under different mappings from latent human capital to observed education level.[12]

We describe trends in intergenerational education mobility over time using the regression specification given in (8). This regression pools all observations in our sample. In this regression, Δ_{i0} (Δ_{i1}) represents the human capital of the parent (child): calculated as education percentiles or alternatively truncated normal expectations. The parameters of interest are α_t, for each time period. The regression contains a limited set of controls (race/gender of child, as well as a constant term), as well as state-year fixed effects ψ_{st}. The coefficients of interest are α_t.

$$\Delta_{i1} = \alpha_t \Delta_{i0} + X_i' \beta_t + \psi_{st} + \varepsilon_i \tag{8}$$

When we aggregate across all states in a year to calculate human capital, we implicitly assume that all states have

[11] These are an intergenerational regression of years of education attained, and a version of that regression with years of education standardized to have mean 0 and standard deviation 1.

[12] Full details are found in Appendix D.

the same educational standards.[13] In reality, different state-level education policies may lead to different mappings between human capital and educational attainment: one state may have the top 20 percent of the human capital distribution attaining a college degree, while in another state it may only be the top 15 percent. Recognizing this limitation, our regression approach accommodates some flexibility in accommodating different educational standards across states, within a given year. We highlight the presence of state-year fixed effects in our regression specification. Hence, our results are not affected if one state has lower educational standards than the others, as long as these differences are consistent across education levels. In contrast, the fixed effects will not address the problem if a state has a relatively high bar for college attainment, but a low bar for high school attainment.[14]

When we compare education mobility across states, the possibility of differing education standards becomes more salient. For this analysis, we estimate separate intergenerational correlations regressions by state-year, following regression specification (9). The controls in X_i are identical to (8). In contrast to (8), child (Δ_{i1st}) and parent (Δ_{i0st}) human capital measures are calculated relative to the marginal distribution for state s and year t. Hence, any differences in α_{st} across states cannot be attributed to differences in state education standards.

$$\Delta_{i1st} = \alpha_{st}\Delta_{i0st} + X_i'\beta_{st} + \varepsilon_i \tag{9}$$

3 Data

The data for this study comes from three longitudinal studies of high school students in the United States. In chronological order, these are the High School & Beyond study (HSB), the National Education Longitudinal Survey (NELS) and the Education Longitudinal Study (ELS). These three studies were conducted by the National Center of Education Statistics (NCES), hence, when referring to all three surveys as a collective, we use the term *NCES surveys*. The HSB and the ELS studied 10th graders in years 1980 and 2002 respectively,[15] In comparison, the NELS surveyed 8th graders in 1988. One implication of this discrepancy is that the NELS cohort includes students who dropped out between 8th and 10th grades, while the other two surveys do not. As a result, we do not include any NELS children who report a final education level less than 10th grade.[16] Putting these three cohorts together, we observe the graduating high school classes in years 1982, 1992, and 2004. From follow-up surveys, we take the last observed value of

[13]Using the notation of (2), the assumption is that δ_{mt} is identical for all states in period t, for every education level m This limitation is analogous to not adjusting for cost of living when measuring income mobility using rank-rank regressions.

[14]Likewise, education standards may differ across races and genders as well.

[15]Both studies also include 12th grader cohorts, which we do not use to make the samples as comparable as possible with the NELS.

[16]Even then, the samples may not be perfectly comparable: consider a student who drops out of high school in 9th grade, and later obtains a GED and some post-secondary education. This student will be observed in the NELS sample but not in the other two. However, we believe that the sample are basically comparable since the conditions outlined above only apply to very few children.

educational attainment to be the terminal value of education for that student. Hence, to be included in our sample, the student must have been surveyed at a late follow-up survey, for observed education levels to reasonably approximate terminal education.[17]

In addition, we drop from our sample any student who is not living with either parent at the initial survey wave. Since students report the education level of their parents, we take this step to remove families where either parent is not involved in the household. Admittedly, this step does not address students who changed families (e.g. were adopted) just before the study, or whose parents separated after the initial study. Separately, we also estimate intergenerational correlations for the subsample of children reporting both parents in the households. This subsample is significantly smaller than our base sample. Sample sizes by survey year and child gender can be found in Table 1.

Within this sample, the marginal distribution of parent and child education shows some changes over time. As Figure 1 shows, the distribution of parent's education has been shifting towards higher education levels, when comparing parents of high schoolers in the 1980 versus the cohort from the 2000s. Here, as in subsequent analysis, we use the maximum across both parents (where both parents are present in the household) as our measure of parental education.[18] Similarly, Figure 5 shows a striking difference between child education distributions in the HSB, relative to subsequent years.[19] In the HSB, there is a much higher percentage of students with terminal high school degrees. One reason for this is the changing marginal distribution of education: across time, it is progressively more common to acquire post-secondary education. However, there is another reason for this discrepancy in post secondary education, which has to do with differences in survey design. Unlike the other two studies, the HSB did not record post-secondary education that did not result in certificate attainment (e.g. college dropouts). Hence, unique to the HSB, respondents who attempted post-secondary education but left before completion are recorded as "HS Grad", and not "some PSE". Given the differences in the way educational attainment is coded between surveys, the method of education percentiles presents another advantage. In each survey year, we are able to use all available levels of educational attainment, without harmonizing the number of categories across different surveys.[20]

[17] The construction of child education variables is discussed in detail in Appendix E.1.

[18] The distribution of parental education is mostly unchanged when using either mother's or father's education, as is the case for our main results.

[19] We compare the marginal distributions of parent and child education against national data drawn from the decennial census (Appendix E.2). Overall, we find that the data are a representative national sample.

[20] The exact coding of parent and child education variables is shown in Table A1.

4 Results

4.1 Linearity of Intergenerational Transmission

Each of our selected methods imposes unverifiable assumptions on the intergenerational transmission process of latent human capital. Before turning to the results, we test one of the more salient restrictions imposed by our model: percentile means/truncated normal expectations should appear to be linearly transmitted in the education data. When we test this assumption, our two empirical approaches do not appear to break the linearity restriction. Figure 2 plots child educational attainment against parent educational attainment, using each of our two empirical specifications. The top panel shows the intergenerational correlation of percentile means: each point displays the expected percentile mean of the child, conditional on the percentile mean of the parent. By inspection, each point lies relatively close to the linear approximation: with few exceptions, the associated confidence intervals for each point overlap with the dotted line of best fit. More formally, we assess linearity of intergenerational transmission using the Ramsey RESET test, (Ramsey, 1969): this test examines the statistical significance of coefficients on higher powers of the parental education variable. In each of the three years of data, it is not possible to reject the hypothesis that child percentile means are linearly dependent on parental percentile means. The intergenerational plots for our alternative approach - truncated normal expectations - are presented in the bottom panel of Figure 2. Once again, based on the observed patterns as well as the statistical test, it is not possible to reject the assumption of linear intergenerational transmission in any of the sample years.

In contrast to our methods, when raw years of education is the specification of choice, the assumption of linear transmission is difficult to maintain. The top panel of Figure 3 shows the intergenerational plot of years of education attained. The deviations from the line of best fit appear to be more significant, and this is corroborated by the Ramsey test: in two out of three years, the assumption of linearity is rejected at the 0.05 level. As the bottom panel of Figure 3 shows, even when years of education are standardized to have mean zero and standard deviation of one, the assumption of linearity is still rejected. Beyond theoretical reasons (capturing relative mobility in underlying human capital), our choice of empirical approach is also motivated by practical concerns of fitting the data.

4.2 Variation across Time

We carry out intergenerational regressions of educational attainment, following regression specification (8), using two measures of observed education - years of schooling, a standardized measure of years of schooling[21] - and two

[21] Within each survey year, child years of schooling is adjusted to have mean 0 and standard deviation 1. The same is done for parent's education.

measures of human capital - education percentiles, and truncated normal expectations.

The main results of our estimation are provided in Table 3.[22] In this table, the focus is on changes in education mobility across time, treating the entire United States as a single geographic unit. Unsurprisingly, parent-child correlations in education are significant in all years, and across the whole range of specifications. On the other hand, the time trends in these coefficients depend on the specification of education variable: specifically, whether changes in the marginal distribution of education have been accounted for. Consider first the results when parent and child education are measured in years attained. As the first column of Table 3 shows, there is a slight decreasing trend in the coefficient from 1982 to 2004. Because the coefficient captures the dependence of child's education on parent's education, the decreasing trend in the coefficients indicates an increase in mobility. These results are the closest analogue to the education mobility trends presented in Hilger (2017). Using an intergenerational regression of years of education attained, Hilger finds that mobility since the 1980s has been declining slightly.[23] While our findings are qualitatively different, we stress that, from one survey year to the next, the changes in our coefficients are slight and not statistically significant.

The second column uses a standardized measure of years: while there is no consistent downward trend, there is a significant fall in the correlation coefficient when comparing the year 1982 with subsequent years. This time, the decrease in correlation coefficient is statistically significant. Both of the naive approaches suggest that mobility in education has increased over these two decades.

Moving to our preferred empirical approaches, the third and fourth columns show, respectively, intergenerational correlation coefficients when education percentiles and truncated normal expectations are used. Both of our preferred approaches undo the effect of changing marginal distributions. When either of these approaches is used, the there is no downward trend in correlation coefficient over the study period. From 1982 to 1992, the coefficient actually increases significantly. On the other hand, from 1992 to 2004, there is a large and significant decrease in the coefficient, resulting in a return to roughly the 1982 level of mobility. This difference suggests that patterns in relative mobility in education are not well captured by using years of education, because of the issue of changing marginal distributions.

In comparison to our preferred methods, consider results from an ordered logit regression, where parental education dummies are the main regressors. The drawback of this method is the relative difficulty of assessing changes in mobility over time. From the significant differences in coefficients in Table 4, it is clear that mobility has changed in the time period we study. However, it is unclear what direction the change in mobility has taken, because the

[22]These results are also shown graphically in Figure 4.

[23]The decline is small for whites and larger for blacks, however, we do not focus on racial differences in mobility in our paper.

comparison has to be made across sets of 3 coefficients. This comparison highlights the advantage of our preferred methods.

Our preferred specifications are most comparable with rank-rank regressions for education, reported in the appendix of Hilger (2017). The empirical method used in his paper is a rescaling of our education percentiles approach. Because the time periods only intersect partially, we compare our results for the 1982 and 1992 graduating classes. In levels, the coefficients for 1982 are similar, however, where our results show a significant decrease in mobility for the 1992 graduating class: Hilger finds a small decrease for blacks and a small increase for whites.[24]

On the other hand, our results are consistent with the general trends in income rank-rank slopes documented in Chetty et al. (2014b). Again, the time periods are only partially intersecting, hence we compare our results for the 1992 and 2004 graduating classes. Qualitatively, there appears to be a decrease in the intergenerational correlation coefficient between these two years.[25] While Chetty et al. study income mobility and we study education mobility, it is likely that national trends would be positively correlated, since income and education are so highly correlated at the level of individual persons.

Since education mobility is affected by a large number of socioeconomic factors, it is not possible to pinpoint a cause for the non-monotone trend in education mobility. One trend that is consistent with our findings is one of parent engagement in schools. Putnam (2000) finds that participation in Parent Teacher Associations declined from 1962 to 1982, and subsequently increased. Hence, it is likely that the class of 1992 experienced lower parent engagement in schools, over the course of their entire K-12 education. If parent engagement in schools is more important for children of less-educated parents, then parent engagement could be an explanation for the trends we find.

Other trends that have been studied in the economics research literature are also likely to have contributed to the education mobility trends we find. These include: motherhood earnings penalties (Dechter, 2014), which have been widening (Waldfogel, 1998) and may disproportionately affect low earning mothers (Budig and Hodges, 2010), changes in family structure (Pew Research Center, 2015) and in fertility, as well as increasing affordability of high-quality colleges (Kinsler and Pavan, 2011).

4.3 Robustness

We check how our results change as we vary several details of the specification. Overall, we find no substantive differences to our main results. First, we examine how stratifying the sample by child gender changes the results. When

[24]There is a small difference in our sample and Hilger's: we do not observe any children who leave high school before grade 10. However, we expect the impact of this difference to be essentially negligible, given the small number of children falling into this category.

[25]Specifically, we compare the 1992 (2004) class to the 1974(1986) birth cohort. This claim still holds if we average the income rank-rank coefficients for the birth cohorts immediately preceding and following.

we separate the sample by gender, we recalculate standardized years and education percentiles, in effect comparing sons to other sons and daughters to other daughters. Alongside this, we also alter our measure of parent education. Our baseline results use the maximum of the two parents' education levels (where both parents are observed in the data). We experiment with only using father's or mother's education. These results are presented in Table A2, and show very similar patterns to our baseline results, for both of our preferred approaches.[26]

Additionally, we examine how our education percentile results change under different definitions of the sample. Our baseline sample contains all parent-child pairs with non-missing child education and at least one non-missing parent education variable. We further restrict the sample to families with two parents in the household, and even further by requiring both parents to report education information. As Table A3 shows, varying the sample does not significantly affect the estimated coefficients: furthermore, the slight changes are mostly in the levels of the coefficients and not the trends. The fourth column of Table A3 shows the results when we use unweighted observations: again, these are quite similar to the baseline patterns. The last column shows results when observations are weighted to be representative at the state, rather than national, level.[27]

We also examine how the different categorization schemes for child education affect our results. In Table A4, the first column contains our baseline results for education percentiles. In the second column, we recode child education to use the same categories in each survey year. This measure of child education ends up only counting completed degree attainment. In the third column, we additionally recode GEDs to be equivalent to high school graduates, since there is some variation in the research literature regarding the equivalence of GEDs to traditional high school degrees. For both of these changes to the baseline specification, our results are not substantially affected. The increase in the intergenerational correlation coefficient from 1982 to 1992 becomes slightly smaller in magnitude. On the other hand, the decrease in this coefficient from 1992 to 2004 becomes more pronounced.

4.4 Dependent and Independent Children

We compare our work to Hilger (2017) in one more respect. The main estimates from the previous work used Census data, which limited the sample of children to those living with their parents (dependent children). Exploiting the NCES data, we study the differences in educational mobility, between dependent children and independent children - those not living with their parents. We estimate separate intergenerational correlation coefficients for each subsample, based on whether the child was observed to be co-residing with at least one parent at the time of the latest follow-up.[28]

[26]When years attained are used as the measure of human capital, there are some differences between the trends by gender of parent and child, which we do not attempt to explain.

[27]These weights are not included in the raw data, and were instead constructed for this study. For details on the construction, see Section E.4.

[28]Depending on the exact survey, the follow-up occurred between 8 and 10 years after the grade 12 year of the child.

The results are presented in Table 5. Between dependent and independent children, the trends are similar, and both are similar to the overall trend. However, there is a difference in the levels of the coefficient: education mobility appears to be higher when only dependent children are studied. This suggests that there are meaningful differences between dependent and independent children relating to mobility.

4.5 Variation across Space

We begin our study of geographic variation at the level of census regions. For this analysis, we retain the pooled national sample and the regression specification for national trend analysis (8), but we allow the coefficient to vary by census region as well as year. The results are presented in Figure 6. Looking first at the results from the intergenerational regression in years attained, there is a general increase in mobility for the Northeast, North and West census regions, which is most pronounced for the West. In contrast, mobility in the South appears to have decreased slightly between 1982 and 2004, although this is statistically insignificant.

Using our preferred methods, we again find that the South appears to be an outlier from the overall pattern of mobility changes. In all other regions, education mobility is higher in 2004 than in 1982. In the South, the opposite is true, and, comparing 2004 with 1982, the decrease in mobility is statistically significant. Within the other census regions, the West stands out for a monotonic increase in mobility across the three survey years. In contrast, the Northeast and North regions appear to be driving the overall mobility trend for the U.S.: decreasing from 1982 to 1992, and increasing from 1992 to 2004.

Moving to finer geographies, we estimate education correlation coefficients separately by state according to regression specification (9): these are summarized in Figure 7.[29] Comparing the peaks of the densities across years, the basic pattern of changes across time are preserved. Additionally, there is significant variation across states, within the same time period. We decompose the variation in intergenerational correlation coefficients into two components: within-state (and across years) and between-state. Table 6 shows that within-state and between-state components contribute in a roughly equal manner towards overall variation in intergenerational correlation coefficients. In contrast to our chosen empirical approaches, a years-on-years regression tends to overstate within-state variation in intergenerational correlation coefficients.

The differences in education mobility across states could come from multiple differences in policy, demographics, or other characteristics. We study one likely influence: the presence or absence of high school exit examinations.

[29] We reiterate that, for this and all subsequent analysis at the state level, human capital measures are calculated relative to the marginal distribution for the particular state-year pair. Additionally, we weight observations to be representative of the state population, rather than the national one. These weights are constructed using decennial Census data. For details, see Section E.4.

The introduction - or increased difficulty - of such examinations is associated with reduced high school completion rates (Warren et al., 2006). Furthermore, some evidence suggests that the impact of failing this examination appears to be disproportionately high for low-income students: they are less likely to pass retake attempts, and hence more likely to leave school without graduating (Papay et al., 2010). Since income and education are positively correlated in the parent population, high school exit examinations could be a barrier against the upward mobility of students from low-education families, and result in lower relative mobility.

We use state-by-year data on the presence of high school exit examinations to test this hypothesis.[30] The exit exam data covers 26 states, over a time period which varies slightly from state to state, but which generally begins in the mid-1970s and ends in the mid-2000s. In order to derive the association between high school exit examinations and educational mobility, we regress our estimated intergenerational correlation coefficients on an indicator for the presence of high school exit examinations (HSEE) for that graduating class. The results are shown in Table 7. Our preferred estimates include state fixed effects, so the coefficient of interest is identified by within-state changes in mobility following the adoption (or removal) of exit examination requirements. We find that the introduction of high school exit examinations is associated with a higher intergenerational correlation coefficient (i.e. lower educational mobility).This trend is not surprising: additional high school graduation requirements are likely to disproportionately affect the more disadvantaged students within that state (i.e. those with less-educated parents). However, while the findings are similar by gender, they are only statistically significant (at the 10 percent level) for male children, and become insignificant when both genders are pooled. Hence, while suggestive, the evidence for the effect of high school exit examinations and education mobility is not strong. Furthermore, once state fixed effects are included, the positive association only appears when using either education percentiles or truncated normal expectations, which underscores the point that changes in marginal distributions could be obscuring meaningful patterns in relative mobility.

4.6 Comparison with Income Mobility

We compare the geographic patterns of education mobility with those for income mobility, taken from (Chetty et al., 2014a). We choose to focus on their measure of relative income mobility: the rank-rank slope. This measure is derived from regressing the parent's rank in the national distribution of income for parents, against the child's rank in the national distribution of income for children. Hence, it is the closest analogue to our educational mobility measures, which also attempt to measure the dependence of the child's rank on the parent's rank, albeit in education instead of income. *A priori*, one would expect that education and income mobility would be closely associated, education is an important determinant of income levels.

[30] Data on high school exit examinations was kindly provided by Rob Warren.

Chetty et al. provide income mobility measures estimated at the MSA level for the 1980-1982 birth cohorts. We match these birth cohorts to the two closest high school graduating classes covered by the NCES surveys, assuming standard grade advancement. These are the classes of 1992 (NELS) and 2004 (ELS), which correspond to the 1974 and 1986 birth cohorts, respectively. In each of these survey years, and for MSAs in which we have sufficient sample size ($N \geq 30$), we generate intergenerational education correlations separately by MSA.[31] We then compare these correlations to the income rank-rank slope, by regressing income correlation coefficients on education correlation coefficients. We find significant positive correlations between income and education coefficients (Table 8). For both of our preferred approaches, our findings imply similar, and substantial, effect sizes: across the cities we sample, a one standard deviation increase in the education correlation coefficient is associated with a half standard deviation increase in the income correlation coefficient. This suggests a close link between the two forms of intergenerational mobility. On the other hand, as the R^2 statistics show, intergenerational correlations in education only explain between 14 and 20 percent of the variation in intergenerational correlations in income.

One weakness of this analysis is the limited coverage of MSAs in the NCES data. The limited coverage calls into question whether the patterns we find are representative of the entire country, especially because the NCES surveys were not designed to provide a representative sample at the MSA level. To check that our results are not sensitive to the sampling of MSAs, we repeat the analysis at the state level. At the state-level, income correlation coefficients are only available for the 1986 birth cohort. We regress these coefficients against the education correlation coefficients we have obtained. First, we include in the regression sample all high school classes for which we have education correlation coefficients.[32] (Table A6, left panel) For a more direct comparison, we next narrow the sample to the class of 2004 (Table A6, right panel). Assuming that high school graduation occurs at age 18, the class of 2004 corresponds to precisely the 1986 birth cohort. In both cases, we still find positive associations between income and education correlation coefficients, at the state level. These findings also yield a similar standardized effect size, which is statistically indistinguishable to the MSA-level analysis. As expected, the strength of the association increases slightly when the sample is restricted to the class of 2004.

4.7 Correlation with Local Characteristics

We examine which characteristics of local geographies are correlated with our measures of education mobility, at the MSA level. While these comparisons are purely associational, they largely show that our educational mobility measures are correlated with local characteristics in the expected manner. In addition, we also compare these associations

[31] For the MSA-level analysis, the human capital measures are calculated with reference to the national distribution.

[32] The regression equation is $\text{Income}_{s,1986} = \alpha + \beta\text{Education}_{s,t} + \phi_t + \varepsilon_{s,t}$ for high school graduating classes $t = \{1982, 1992, 2004\}$. The coefficient of interest is β.

to analogous ones using income correlation coefficients instead of education. Local characteristics were gathered from decennial census data, available on IPUMS (Ruggles, 2010). In addition to these basic characteristics, we also consider residential segregation indices within each MSA, calculated using the Neighborhood Change Database (NCDB).[33]

To ensure adequate sample size within each MSA, we pool children of both genders within each MSA, and estimate MSA-specific intergenerational correlation coefficients. Next, we pool all years of data and run univariate regressions of these coefficients against the selected MSA characteristics, including survey year fixed effects. Hence, the results describe the correlation between education mobility and other local characteristics across cities rather than across time.[34] For comparison, we also perform similar regressions with intergenerational correlation coefficients for income, taken from Chetty et al. (2014a).[35] Table 9 diplays these results.

In terms of correlation with local characteristics, our preferred specifications yield similar patterns to a conventional intergenerational regression of years attained. On the other hand, education mobility and income mobility are not always affected in the same way by local characteristics. Racially segregated cities and cities with small child populations are both associated with both lower income mobility as well as lower education mobility. On the other hand, a greater fraction of minorities within an MSA is associated with lower income mobility but higher education mobility.[36] While we cannot provide a definite reason for this divergence, it is possible that areas with more minorities promote social mobility in education policy, while simultaneously being characterized by labor market factors that impede mobility (e.g. racial discrimination in employment).[37]

5 Conclusion

In this paper, we develop a method of estimating intergenerational correlations in educational attainment. This method is tailored to categorical variables, furthermore, it allows for easy comparison of coefficients. This method allows for estimates of mobility even when intergenerational earnings data are poor or unavailable. Implementing this method, we show that educational mobility seems to have slightly increased for young adults who left high school between 1982

[33]The calculation of segregation indices requires the racial composition of neighborhoods within each MSA - a higher level of geographical detail than is available on IPUMS. Hence, for these indices, we turn to the Neighborhood Change Database (NCDB), which provides information at the tract-level. Further details on the construction of local characteristics can be found in Appendix E.3.

[34]We experimented with additionally including state effects: while the coefficients were roughly unchanged, there was a large loss in precision. We do not present these results.

[35]We analyze two sets of income correlation coefficients. The first set restricts the sample of MSAs to those in the NCES sample. The second set includes all MSAs from the Chetty et al. (2014a) sample. Between these two samples, the associations with local characteristics are quite similar, which also suggests that the sample of MSAs in the NCES sample is fairly representative. The exception to this is with the measure of the segregation of the rich.

[36]In Chetty et al. (2014a), there is a significant negative relationship between inequality and mobility, which we fail to replicate here. There are two likely reasons for this: we use MSAs instead of commuting zones as the geographical area, and our income gini statistics are calculated from census data instead of tax return data.

[37]A similar explanation could also explain why we find no association between fraction of single parents (s a measure of family instability) with education mobility, even though there is a strong negative association between this variable and income mobility.

to 2004, although the trend is non-monotone. In addition, there is substantial geographical variation in educational mobility, and it tends to be positively correlated with income mobility, as expected. We found important regional differences in mobility, with the South less mobile than other regions and failing to increase mobility during this time period.

We have only begun to explore associations between educational mobility and local characteristics and policies. We found that state level high school examinations are correlated with lower mobility over this period and also outlined a set of correlations between community characteristics and mobility that should be the subject of future research.

Tables

Table 1: Sample Size Description

	1984		1992		2004	
	Sons	Daughters	Sons	Daughters	Sons	Daughters
Total observations	5810	6240	11390	11840	7520	7590
Child education observed	5650	6090	5040	5800	6030	6640
Baseline: 1+ Parent in household (education observed)	4630	5050	4550	5210	5783	6350
Both parents in household	3600	3680	3430	3790	3680	3980
Both parents' education observed	3050	3120	3360	3730	3680	3980
Baseline MSA Sample: at least 50 surveyed	3570	3910	3880	4450	4480	4961
Baseline Sample	9680		9770		12130	
Total			31580			

Notes:
Sample counts rounded to nearest 10.
Data: HSB (1982), NELS (1992), ELS (2004). Years denote high school graduating class.
Sample restrictions are cumulative.
NELS: Total observations for base year survey. Fewer than 14000 observations
were subsequently resurveyed late enough to assess final education.

Table 2: Descriptive Statistics of Sample

	Race				Education			Parent in Household		
	Female	Black	Hispanic	Other	Years	High School	College	Father	Mother	Both
1982	0.52	0.12	.	0.12	13.4	0.89	0.28	0.79	0.96	0.75
1992	0.53	0.085	0.12	0.10	14.1	0.94	0.36	0.77	0.97	0.74
2004	0.52	0.12	0.14	0.15	14.3	0.96	0.39	0.69	0.94	0.63
Total	0.52	0.11	0.13	0.12	13.9	0.93	0.34	0.75	0.95	0.70

	Parent Education								
	Father			Mother			Maximum of Both Parents		
	Years	High School	College	Years	High School	College	Years	High School	College
1982	13.1	0.75	0.23	12.7	0.79	0.15	13.5	0.34	0.25
1992	13.6	0.85	0.29	13.0	0.86	0.19	13.8	0.20	0.29
2004	14.0	0.88	0.34	13.7	0.88	0.29	14.8	0.19	0.43
Total	13.6	0.83	0.29	13.2	0.85	0.21	14.1	0.24	0.33

Notes:
Data: HSB (1982), NELS (1992), ELS (2004).

Table 3: Education Intergenerational Regression Coefficients

	Years Education	Years (standardized)	Education Percentile	Truncated Normal
1982	0.281	0.386	0.354	0.362
	(0.010)	(0.014)	(0.010)	(0.011)
1992	0.263	0.301	0.463	0.488
	(0.033)	(0.039)	(0.015)	(0.019)
2004	0.255	0.329	0.325	0.326
	(0.013)	(0.017)	(0.010)	(0.010)
p-value: 1982 = 1992?	0.605	0.042	0.000	0.000
p-value: 1992 = 2004?	0.825	0.499	0.000	0.000
p-value: 1982 = 2004?	0.129	0.012	0.068	0.018
N	30720	30720	30720	30720

Notes:
Column headings denote categorization of education variable used in intergenerational regression.
Education Percentile = [(number with strictly less education) + 0.5(number with equal education)]/(total number).
Truncated Normal: conditional expectation of latent continuous variable, based on observed education category, and assuming latent variable takes standard normal distribution.
Parent education: maximum of both parents.
Sample: children of both genders, with non-missing education and at least one parent with non-missing education.
Observations weighted for national representation. Displayed number of observations rounded to nearest10.
Controls: child race, child gender, state fixed effect.
Standard errors generated by bootstrap.

Table 4: Education Intergenerational Regression - Ordered Logit Marginal Effects

	Graduating Class of Child		
	1982	1992	2004
HS Grad.	0.039	0.135	0.156
	(0.003)	(0.012)	(0.011)
Some Post HS	0.077	0.243	0.236
	(0.006)	(0.012)	(0.012)
Coll. Grad.	0.291	0.575	0.450
	(0.018)	(0.025)	(0.016)
N		29900	

Notes:
Displayed estimates are marginal effects on probability of reaching highest category (college graduate).
Parent education measured as maximum of both parents.
Children of both genders included.
Sample: all families where specified parent is in household, with non-missing education.
Observations weighted for national representation. Displayed number of observations rounded to nearest 10.
Controls: child race, child gender, state fixed effect.
Standard errors generated by bootstrap.

Table 5: Education Intergenerational Regression Coefficients: Comparing Dependent and Independent Children

	Education Percentile			Truncated Normal		
	All Children	Independent	Dependent	All Children	Independent	Dependent
1982	0.354	0.398	0.263	0.362	0.399	0.274
	(0.010)	(0.012)	(0.019)	(0.011)	(0.010)	(0.019)
1992	0.463	0.472	0.390	0.488	0.498	0.405
	(0.015)	(0.020)	(0.032)	(0.019)	(0.020)	(0.033)
2004	0.325	0.342	0.261	0.326	0.343	0.263
	(0.010)	(0.012)	(0.022)	(0.010)	(0.012)	(0.025)
p-value: 1982 = 1992?	0.000	0.004	0.001	0.000	0.000	0.000
p-value: 1992 = 2004?	0.000	0.000	0.000	0.000	0.000	0.001
p-value: 1982 = 2004?	0.068	0.001	0.945	0.018	0.001	0.709
N	30720	20890	7330	30720	20890	7330

Notes:
Dependent (independent) children are those residing (not residing) with a parent, 8-10 years after high school graduation.
Education Percentile = [(number with strictly less education) + 0.5(number with equal education)]/(total number).
Truncated Normal: conditional expectation of latent continuous variable, based on observed education category, and assuming latent variable takes standard normal distribution.
Parent education: maximum of both parents.
Sample: children of both genders, with non-missing education and at least one parent with non-missing education.
Observations weighted for national representation. Displayed number of observations rounded to nearest 10.
Controls: child race, child gender, state fixed effect.
Standard errors generated by bootstrap.

Table 6: Variation in Education Intergenerational Correlation Coefficients: Within vs Between State

	Years		Education Percentile	Truncated Normal
	raw	standardized		
SD - Within State	0.25	0.30	0.08	0.08
SD - Between States	0.18	0.22	0.10	0.10
Fraction Variance from Between	0.17	0.24	0.46	0.45
Observations	123	123	123	123

Notes:
Each observation is one intergenerational correlation coefficient, estimated separately for each state x year. Sample includes children of both genders.
Columns denote categorization of education used in intergenerational regression.
Where relevant, parent/child education is measured relative to the respective state distribution.

Table 7: Regression of Education Intergenerational Correlation Coefficients on State High School Exit Examination Presence

	Years		Percentile	Normal	Years		Percentile	Normal
	raw	standardized			raw	standardized		
Pooled Child Genders	0.0608*	0.0744*	0.0522	0.0499	0.0381	0.0430	0.0706	0.0656
	(0.0234)	(0.0297)	(0.0337)	(0.0338)	(0.0332)	(0.0413)	(0.0432)	(0.0434)
Observations	69	69	69	69	69	69	69	69
Sons	0.0659*	0.0715*	0.0396	0.0383	0.0487	0.0615	0.0876+	0.0897+
	(0.0291)	(0.0332)	(0.0422)	(0.0402)	(0.0310)	(0.0400)	(0.0434)	(0.0499)
Observations	63	63	63	63	63	63	63	63
Daughters	0.0639*	0.0786*	0.0628	0.0433	0.0505	0.0577	0.0751	0.0716
	(0.0292)	(0.0379)	(0.0421)	(0.0436)	(0.0477)	(0.0602)	(0.0571)	(0.0579)
Observations	64	64	64	64	64	64	64	64
State FE	No	No	No	No	Yes	Yes	Yes	Yes
Marginal Distributions			National	State			National	State

Notes:
Each observation is a regression coefficient from a state x year specific intergenerational regression.
Columns differ by categorization of education used.
Parental education measured as maximum of both parents'.
Percentile = [(number with strictly less education) + 0.5(number with equal education)] / (total number)
Education variables calculated using parent/child position in respective state distribution.
Normal: conditional expectation of latent continuous variable, based on observed education category, and assuming latent variable takes standard normal distribution.
Rows display results from different child samples: pooled and separate by gender.
High school exit exam variable: indicator for presence during graduating year of sample.

Table 8: Regression of Intergenerational Correlation Coefficients (Income on Education)

	Years Attained		Education Percentile		Truncated Normal	
	1992	2004	1992	2004	1992	2004
IG Correlation, Education	0.287**	0.166**	0.171*	0.160**	0.159*	0.148**
	(0.0848)	(0.0598)	(0.0648)	(0.0467)	(0.0587)	(0.0414)
Mean (S.D.), Education Coefficient	0.25	0.22	0.44	0.29	0.46	0.29
	(0.23)	(0.12)	(0.13)	(0.16)	(0.14)	(0.16)
Mean (S.D.), Income Coefficient	0.35 (0.05)					
R^2	0.264	0.138	0.179	0.197	0.187	0.209
Observations	34	50	34	50	34	50

Notes:
Each observation is one MSA. Excludes MSAs with sample size below 30.
Parental education measured by maximum over both parents.
Income coefficient: rank-rank slope of 1980-1982 birth cohorts and their parents.
Column headings show categorization of education used to obtain intergenerational correlation coefficient. Coefficients estimated using children of both genders.
Education Percentile = [(number with strictly less education) + 0.5 * (number with equal education)] / (total number).
Truncated Normal: conditional expectation of latent continuous variable, based on observed education category, and assuming latent variable takes standard normal distribution.
Class of 1992 (2004) represents 1974 (1986) birth cohort.
In secondary regression, education coefficients weighted inversely by standard error.

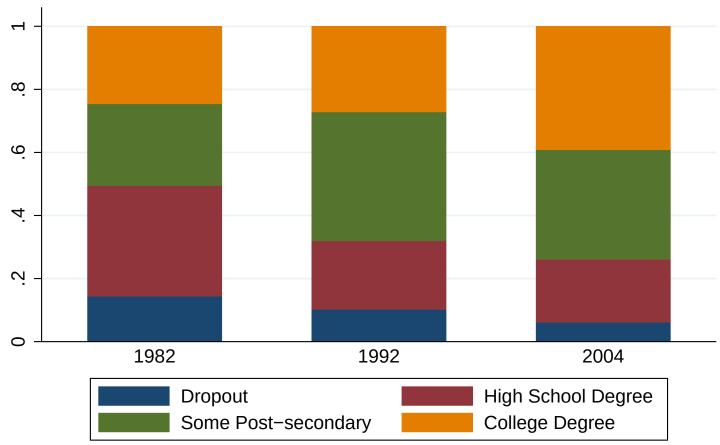
Table 9: Correlations between Education IG Coefficient and MSA Characteristics

	Education IG Correlation			Income Rank Slope	
	Years Attained	Education Percentile	Truncated Normal	Restricted Sample	Full Sample
Log. Family Income	0.02	0.13	0.11	0.11	-0.12^{+}
	(0.15)	(0.19)	(0.19)	(0.09)	(0.06)
Income Gini	-0.10^{+}	-0.09	-0.12*	0.08	0.09
	(0.05)	(0.06)	(0.06)	(0.10)	(0.07)
Segregation of Rich (above 50k income)	-0.17**	-0.12	-0.11	-0.35**	0.03
	(0.06)	(0.08)	(0.08)	(0.08)	(0.06)
Segregation of Poor (below 10k income)	0.08	0.08	0.12^{+}	0.43**	0.40**
	(0.06)	(0.07)	(0.07)	(0.08)	(0.06)
Fraction Minority	-0.13**	-0.13*	-0.16**	0.09	0.19**
	(0.05)	(0.06)	(0.06)	(0.11)	(0.06)
Segregation of Minorities	0.19**	0.22**	0.24**	0.65**	0.63**
	(0.05)	(0.06)	(0.06)	(0.07)	(0.05)
Fraction under 5	-0.16*	-0.14	-0.15^{+}	-0.37**	-0.18**
	(0.07)	(0.08)	(0.08)	(0.08)	(0.06)
Fraction above 65	0.09	0.05	0.07	0.20*	0.11^{+}
	(0.06)	(0.07)	(0.07)	(0.09)	(0.06)
Fraction Single Parent	0.00	-0.01	-0.01	0.31**	0.42**
	(0.08)	(0.10)	(0.09)	(0.09)	(0.06)
Observations	134	134	134	111	231
High School Graduating Class	1982, 1992, 2004	1982, 1992, 2004	1982, 1992, 2004	2004	2004
Year Effects	Yes	Yes	Yes	No	No

Notes.
Each observation is one MSA x year.
Dependent variable: Intergenerational correlation coefficient, obtained from separate regressions by MSA x survey year.
Column headings show categorization of education used in intergenerational regression.
Education Percentile = [(number with strictly less education) + 0.5(number with equal education)]/(total).
Truncated Normal: conditional expectation of latent human capital, based on observed education, and assuming latent variable takes standard normal distribution.
Parent education measured from maximum of both parents. Child: sons and daughters.
Dependent variable and MSA characteristics standardized to mean 0, sd 1.

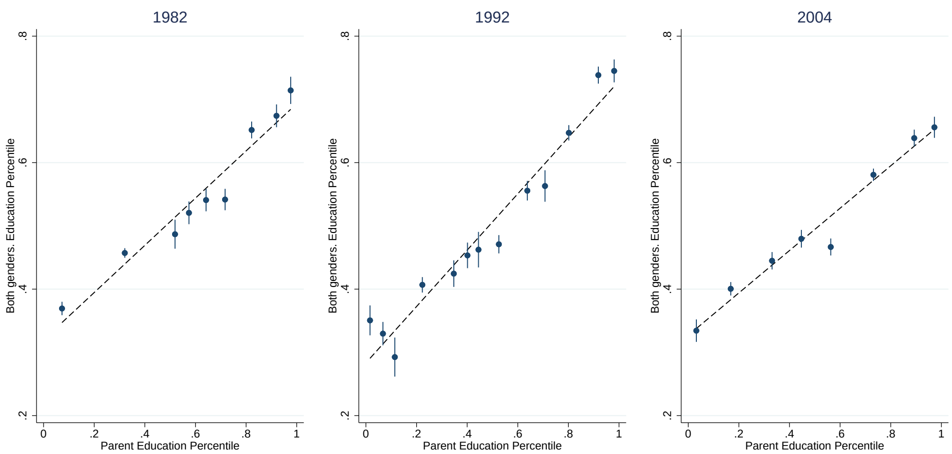
Figures

Figure 1: Marginal Distribution of Parental Education across Years

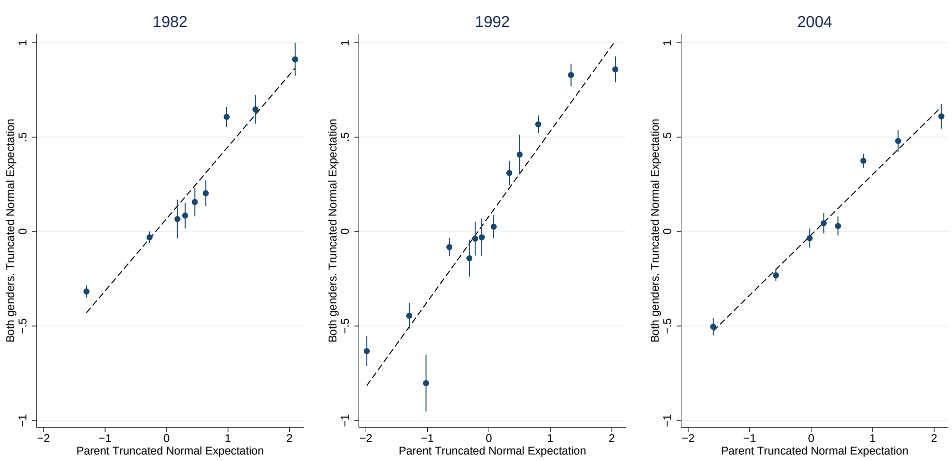


Years denote high school graduating class.
Data: HSB (1982), NELS (1990), ELS (2004).
Observations in data weighted for national representation.
Parental education measured by maximum of both parent's.

Figure 2: Intergenerational Plot of Education Percentiles (top) and Truncated Normal Expectations (bottom)

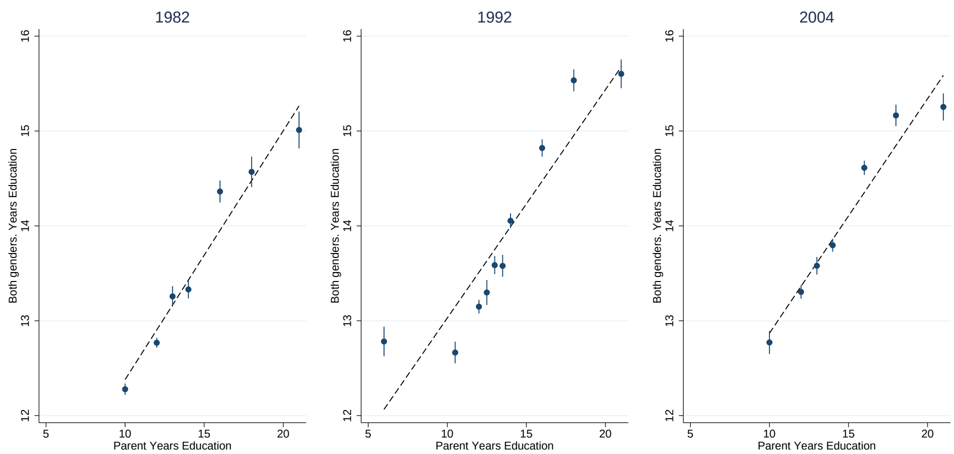


Parent education measured by maximum of both parents.. Child: Both genders..
Education Percentile: [Obs. with strictly lower education + 0.5 * Obs. with equal education] / (Total obs.)
Ramsey RESET Test for non−linearity, p−values: 1982 = 0.14, 1992 = 0.11, 2004 = 0.43.

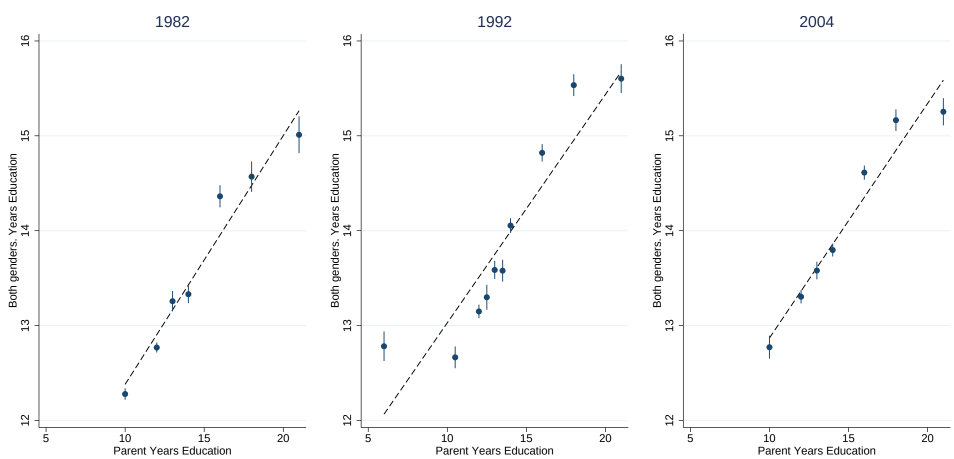


Parent education measured by maximum of both parents.. Child: Both genders..
Truncated Normal Expectation: Truncated normal expectation computed assuming that latent human capital ta
Ramsey RESET Test for non−linearity, p−values: 1982 = 0.33, 1992 = 0.18, 2004 = 0.58.

Figure 3: Parent-Child Intergenerational Plot of Years Attained: Raw (top) and Standardized (bottom)

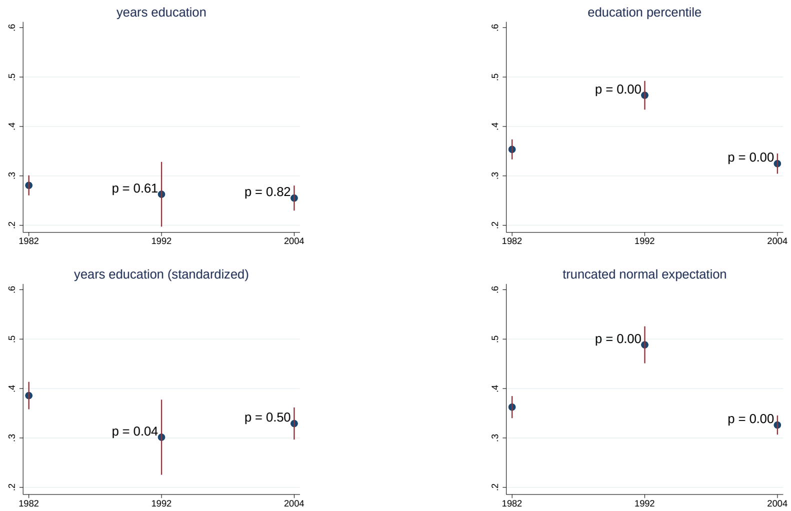


Parent education measured by maximum of both parents.. Child: Both genders..
Years Education: Some years imputed based on partial degree completion.
Ramsey RESET Test for non−linearity, p−values: 1982 = 0.40, 1992 = 0.00, 2004 = 0.05.



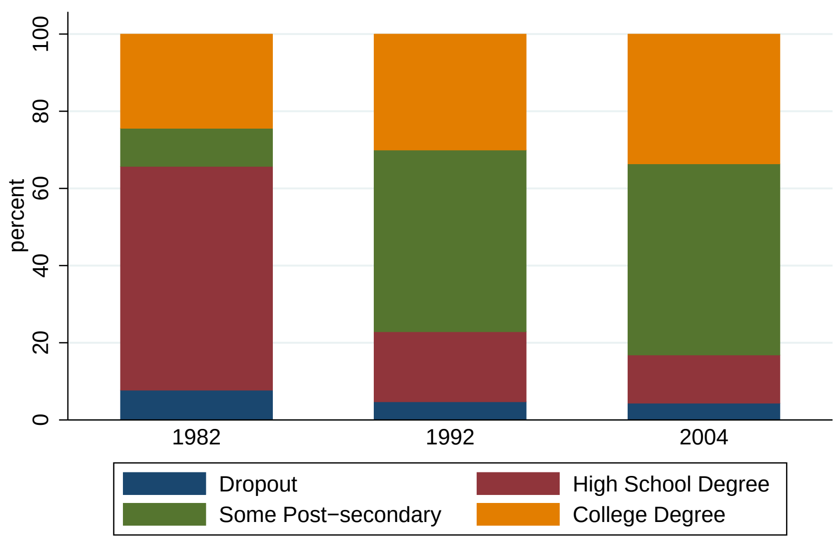
Parent education measured by maximum of both parents.. Child: Both genders..
Years Education: Some years imputed based on partial degree completion.
Ramsey RESET Test for non−linearity, p−values: 1982 = 0.40, 1992 = 0.00, 2004 = 0.05.

Figure 4: Education IG Correlation Coefficients over Time



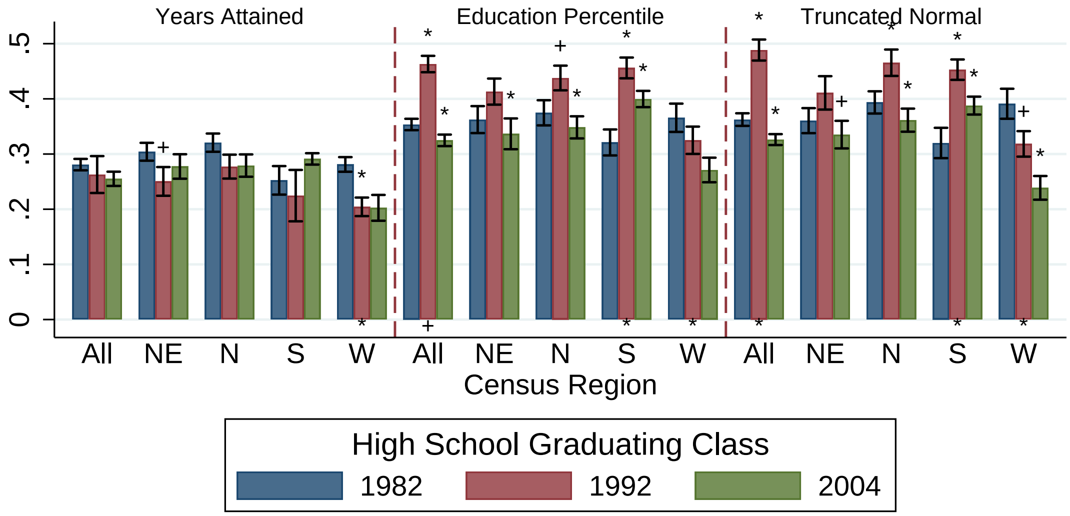
Graph titles indicate education variable used in intergenerational regression.
Education Percentile = [(number with strictly less education) + 0.5(number with equal education)]/(total numbe
Truncated Normal Expectation: expectation of latent continuous variable, conditional on observed education c
Observations weighted for national representation. Parental education measured as maximum of both parents
Sample: all families where specified parent is in household, with non−missing education.
Controls: child race, child gender, state fixed effect.
95% confidence intervals shown.
P−value of test for equality, between this survey year and previous survey year.

Figure 5: Marginal Distribution of Child Education across Survey Years



Years denote high school graduating class.
Data: HSB (1982), NELS (1990), ELS (2004).
Observations in data weighted for national representation.

Figure 6: Education IG Correlation Coefficients by Region



Graph titles indicate education variable used in intergenerational regression.
Education Percentile = [(number with strictly less education) +
0.5(number with equal education)] /(total number).
Truncated Normal: conditional expectation of latent continuous variable, based on observed education category, and assuming latent variable takes standard normal distribution.
Sample: children of both genders, with non−missing education and at least one parent with non−missing education.
Parental education measured using maximum of both parents.
Controls: child race, gender, state fixed effect. Standard errors clustered by state.
Significance stars − Above: test of equality between current and previous survey year.
Below: test of equality between first and last survey year. (+ 0.1 * 0.05)

Figure 7: Distribution of State-specific Education Mobility Coefficients

Coefficients from intergenerational regression of education percentiles. Parent/child education is measure
Coefficients estimated separately for each state x year.
Parental education measured as maximum of both parents'.
Sample: children of both genders.
In plotting density, coefficients weighted inversely by their respective standard error.

A Derivation of Intergenerational Human Capital Regression

The model outlined here is very close to that of Solon (2004), with some changes to the technology of human capital production in order to generate the linear functional form. Each parent can spend (after-tax) income on consumption or invest in the human capital of the next generation (10). This investment is converted into human capital using a linear technology (11). Aside from private investment, human capital also depends on government investment. Finally, parental income is also linear in parental human capital (12).

$$(1-\tau)y_{ig} = c_{ig} + I_{i,g+1} \tag{10}$$

$$h_{ig} = \nu + \theta I_{ig} + G_{ig} + e_{i1} \tag{11}$$

$$y_{ig} = \mu + \rho h_{ig} \tag{12}$$

Parents maximize utility based on Cobb-Douglas preferences (Equation (13)), which leads to investment which is linear in parental human capital (14). Finally, because of the linear technology of human capital, child human capital is also linear in parental human capital (15).

$$U_{i0} = (1-\alpha)\log c_{i0} + \alpha \log h_{i1} \tag{13}$$

$$I_{i1} = \alpha\theta(1-\tau)(\mu + \rho h_{i0}) - (1-\alpha)(\nu - e_{i1} - G_{i1}) \tag{14}$$

$$h_{i1} = \alpha\theta(\nu + \theta(1-\tau)\mu) + \alpha\theta^2(1-\tau)\rho h_{i0} + (1+\theta+\alpha\theta)(G_{i1} + e_{i1}) \tag{15}$$

B Numerical Example

To best understand the issue with changing marginal distributions, we focus on an example where the child's human capital is perfectly observed (and continuous). However, only (discrete) parental education is observed. This simplification is made to focus attention on the marginal distribution of parent's education, and the problem described holds when only child education is observed as well.

In this example, the marginal distribution of parental education changes over time. Hence, human capital is denoted as $h_{i,g,t}$, for family i, generation g, and year t. In both time periods $t = 1, 2$, the underlying relationship between parental human capital and child human capital is identical:

$$h_{i,1} = h_{i,0} + \varepsilon_i$$

In time period 1, parental human capital is distributed as follows: $h_{i,0,t} \sim U(10, 20)$. In time period 2, the distribution has shifted to the right: $h_{i,0,1} \sim U(11, 21)$. Thus, between these two time periods, parental human capital undergoes a general increase.

While $h_{i,1,t}$ is observable to the researcher, $h_{i,0,t}$ is not. Instead, only $e_{1,0,t}$ is observed:

$$e_{i,0,t} = \begin{cases} 1 & h_{i,0,t} <= 12 \\ 2 & h_{i,0,t} \in (12, 16] \\ 3 & h_{i,0,t} > 16 \end{cases}$$

In the situation described above, education standards (e.g. college admission requirements) are not changing, but parental human capital is increasing. As a result, more parents from year 2 attain high levels of education.

With this setup, estimating the equivalent of (3) for each year will yield the following coefficients $\{\beta_{j,t}\}$, where j indexes level of education:

$$\begin{aligned} \beta_{1,1} &= 11 & \beta_{1,2} &= 11.5 \\ \beta_{2,1} &= 14 & \beta_{2,2} &= 14 \\ \beta_{3,1} &= 18 & \beta_{3,2} &= 18.5 \end{aligned}$$

This example highlights two issues. First, with a set of three intergenerational coefficients per year, it is difficult to make a comparison and determine which year had higher mobility. Second, in our judgment, the estimated mobility coefficients should be identical across years, because the relative position of parents within the distribution still exerts the same influence on the child's relative position. The discrete nature of education provides the appearance of a change, because the shifts in the distribution of parental education are not accounted for.

Finally, in the above example, it is the distribution of parental human capital that shifts. However, in an observationally equivalent manner, The change in coefficients could be caused be a combination of educational standards changing, i.e. $e_{i,0,1} \neq e_{i,0,2}$, and the distribution of human capital changing. For example, keeping all features of year 1 the same, but changing parental human capital and education standards to the following:

$$h_{i,0,2} \sim U(10,22) \qquad\qquad e_{i,0,2} = \begin{cases} 1 & h_{i,0,2} <= 13 \\ 2 & h_{i,0,t} \in (13,15] \\ 3 & h_{i,0,t} > 15 \end{cases}$$

results in the same set of estimated coefficients.

C Alternative Measures of Mobility in Education

In measuring mobility, there is inevitably some loss in reducing a complex phenomenon to a single parameter. The discrete nature of education presents some additional challenges. These challenges will become apparent when we turn to some descriptive statistics in the data.

In this section, we discuss some alternative ways to measure mobility that have been employed in the literature. In general, these methods are problematic, when it comes to making comparisons across different periods/cities. The papers that are cited in this section have not focused on such comparisons.

C.1 Ordinal Variable Regressions

One response to the discreteness of education data is to use ordinal variable regressions: e.g. the ordered logit. This approach solves, in a straightforward manner, the issue of the child marginal distribution. If, for example, college admissions standards decrease from one year to the next, the estimated cut-points for the ordered logit will shift downwards in the second year.

However, it is not only the marginal distribution of child's education that is changing - the marginal distribution of parent's education is changing as well. Figure 1 documents evidence of such changes. For the HSB onwards, the changes in the marginal distribution of father's education show no clear pattern. However, the changes appear to be non-negligible.

The changing marginal distribution of parent's education is not directly addressed by the standard ordinal variable regression. It is in the treatment of parent's education, not the child's, that our approach is distinct from ordinal variable regressions.

Furthermore, as prior studies have shown, the use of an ordinal variable regression does not address the issue of non-linearity in years attained (Nguyen et al., 2005). Hence, in this context, it is still costly to approximate parental educational attainment by years attained.

C.2 Transition Matrices

One way of depicting mobility is to look at a transition matrix across generations, otherwise known as a mobility matrix. Table A7 presents mobility matrices, roughly ten years apart. Since education is discrete and relatively sparse, terminal educational attainment is aggregated into 4 categories. (dropouts, high school graduates, some post-secondary education, college degree) The transition matrices shown are size transition matrices, because they use absolute categories.

Table A7 suggests an increase in the average level of education. In principle, to measure mobility as a relative concept, percentiles of education could be used in order to generate a quantile transition matrix. Practically, the sparseness of education means that percentiles are not very meaningful. However, the table should also suggest that a comparison of two mobility matrices is difficult, and hence some sufficient statistics are desirable. Some such measures that are commonly used are given in Table A8.

Broadly speaking, these matrix-based measures can be broken down into two categories: eigenvalue measures and off-diagonal measures. We find both of these to be unsuitable for dealing with education data, for different reasons. The eigenvalue measures are unsuited to measuring changes in mobility because they assume a stationary process and measure the time taken for the intergenerational process to become independent of initial conditions (i.e. the marginal distribution of education). For comparisons across time, it is assumed that the process itself might be changing, and hence the time taken to depart from initial conditions is not of importance. Furthermore, such measures ignore mobility once the stationary distribution has been attained.

When applied to absolute categories (as opposed to relative quantiles), the off-diagonal measures are poorly suited to the measurement of mobility for another reason: they conflate differences in marginal distributions with differences in mobility. For example, consider the following matrices A and B:

$$A = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad B = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

These two matrices are very similar. In A, a child achieves the exact same level of education as his parent. In B, the child achieves a level of education that is a single level above his parent's. Assuming that children of highly educated parents stay in the top category, there is some pooling at the top, but otherwise the society is still highly immobile: parents in the lowest education category never send their children out of the lowest level of education within the child's generation. However, off-diagonal measures of mobility will record a substantial increase in mobility. In the case of M_1, this change is 0 to 1. Under some regularity assumptions on the underlying process, this change represents the maximal possible change in the mobility index (Shorrocks, 1978).

Essentially, the problem arises because education mobility matrices must be constructed using absolute categories. When the child marginal distribution is not the same as the parent marginal distribution, the mobility matrix interprets this shift as a change in mobility. To some researchers, this interpretation of mobility is not problematic. However, because one of our objectives is to compare education mobility with income mobility, we prefer to retain the notion of relative mobility in our estimates.

Unlike our approach, transition matrices offer the ability to focus on particular aspects of mobility. For example, the probability that the child of high school dropouts becomes a college graduate is one element of the transition matrix, and the probability that the child attains a higher education level than their parent is a function of several elements of that matrix. Because we choose to focus on relative mobility as a general concept, we do not make use of this feature.

D Comparison of Methods Using Simulated Data

To compare each empirical approach, we simulated 250 families, each with a single parent and a single child. Parents' human capital $h_{i,0}$ is drawn from the standard normal distribution. Child human capital $h_{i,1}$ is a weighted sum of parents' human capital and an idiosyncratic shock, which is distributed i.i.d. standard normal (16). The intergenerational correlation between parent and child human capital is 0.25.

$$h_{i,1} = 0.25\, h_{i,0} + 0.75\, \varepsilon_i,\; \varepsilon_1 \sim \mathrm{N}(0,1) \tag{16}$$

We simulate discrete orderings of human capital into education levels in two different time periods. In each time period, we use the same draws of human capital. However, each time period has a different categorization of latent human capital into four discrete education levels, for parents and for children. Table A9 describes these categorizations. In the simulated data, the marginal distribution of parent and child human capital follows the standard normal distribution. Table A9 presents the minimum quantile of this distribution needed to attain a particular education level in a given time period. These quantiles were chosen to closely match the marginal distributions of parent and child education we observe in the data.

We estimate intergenerational correlations using four different empirical approaches. Figure A2 presents the results. Before addressing the empirical approaches, we present estimated intergenerational correlations under an unrealistic scenario: when latent human capital is observed. In this scenario, the estimated parameters are close to the true value, moreover they are - by construction - identical to each other. Moving to feasible empirical approaches, we first consider an intergenerational regression of years of education. In both time periods, the point estimates are relatively close to the true parameter. However, the difference between the estimates in both time periods is relatively large, such that the standard errors do not overlap. Since our research objective is to document trends in relative mobility over time, as well as patterns across geographics, the size of the difference is a cause for concern. When a standardized measure of years is used instead, the difference in estimated parameters remains large.

In contrast, using our chosen empirical approaches (education percentile and truncated normal expectations), the estimated parameters vary less across time periods. Relative to the standard error, the difference in coefficients across time periods appears to be negligble. In our view, this is the main advantage presented by our chosen methods. Additionally, we note that using both of our methods, and in both time periods, it is not possible to reject the hypothesis of the true parameter.

E Data

E.1 Derivation of Education Variables

For all three surveys, parental education variables are measured at the baseline survey. The construction of these variables is relatively straightforward: they are taken directly from the raw data. The rest of this section will describe the construction of child education variables: this is more complicated because child education information is elicited across multiple survey waves, with different levels of specificity.

For the HSB, child education variables are taken from the wave 5 survey, administered in 1992. In this survey, two questions are important. The first is whether the respondent obtained a high school degree by 1986 (four years after the normal graduation date). The second question asks about the level, if any, of post-secondary education possessed at the time of survey. If either response is missing, the observation is dropped, because the final level of educational attainment is unclear. Additionally, if the response to the post-secondary education question is "None", and the question about high school degree is missing, then the exact level of education is similarly unclear. In this case, degree attainment information from the wave 4 survey (1986) is used to infer educational attainment at high school graduate and below. Where the wave 4 response is missing, we also drop the observation. While the wave 4 question could also be used for information on higher education levels, there is a high chance that the responses for higher education levels will not represent terminal levels of education.

For the NELS, child education variables are constructed using the 4th follow-up survey (2000) as a starting point. Our child education variables are again constructed from two variables in the source data. The first variable concerns post secondary education as of the year 2000. For respondents with no post-secondary experience, this variable is coded as missing. In this case, child education is filled in using a second question about the high school degree / GED attainment of the child, again as of year 2000. This question allow identifies dropouts, but does not differentiate between GED and conventional high school degree recipients. For this, we obtain the relevant information from a pair of questions about high school diploma type. This question was first asked in the 3rd follow-up (1994) and also in the 4th follow-up, for respondents who had completed such a degree.

For the ELS, the basis for our child education variable is the educational attainment question in the 3rd follow-up (2012). This variable is supplemented by a GED attainment variable from the same follow-up. Finally, a small number of respondents were dropouts at the 2nd follow-up (2006) and missing at the 3rd follow-up; we count these respondents as dropouts as well.

E.2 Marginal Distribution of Education

In order to make a comparison with the NCES surveys, data on parents was drawn from the decennial census (years $1980-2000$), downloaded from IPUMS (Ruggles, 2010). Each census year was matched to the closest NCES survey (i.e. the 1980 census was matched to the HSB, etc.)

Within each census year, household heads reporting at least one child, along with their spouses, formed the basis for our sample. Refining this sample, we created a more comparable sample based on the age of the children. In order to do so, we aasumed that children graduate from highschool at age 18, and calculated the age the child would have been during the year the census was taken. Finally, since the census data only reports the age of the eldest and youngest child, parents were included in the final sample as long as the age interval between the eldest and youngest child spanned the appropriate age.

Table A10 presents the results of the comparison for parents. The best comparison can be made for the percentages under "Dropout" and "Coll grad", because these categories are directly comparable between NCES survey and census. In contrast, the percentages for "HS Grad" and "some PSE" are not suited for comparison - in the census, only degree attainment counts as post-secondary education, and other forms of post-secondary education are treated as "HS Grad".

On the other hand, in the NCES surveys, incomplete post-secondary education is separated from non-attempt, to varying degrees.

Restricting the comparison to the two specified categories, the marginal distributions of parental education appear to be quite similar, between the NCES surveys and the census. The worst match comes from Mothers, in 1982, where the discrepancy is dropout rates is 7 percentage points.

E.3 Local Characteristics

The variables in Table 9 are taken from the Neighborhood Change Database (NCDB). The NCDB contains tract-level statistics based on Census data. Because data is only available in decennial census years, we match the survey base year to the closest census year. The meaning of most of the variables is straightforward, save for the isolation and dissimilarity indices. The dissimilarity index measures how uniformly different groups (whites and minorities) are distributed across neighborhoods (a neighborhood in our sample corresponds to the census tract). It takes values between zero and one, and higher values mean less uniform distribution. Denoting neighborhoods within an MSA by n, the dissimilarity index is calculated as:

$$\frac{1}{2}\sum_{n=1}^{N}\left|\frac{w_n}{W}-\frac{m_n}{M}\right|$$

where w_n denotes the number of whites in a neighborhood and $W = \sum_n w_n$, and respectively for minorities m.

E.4 State Weights

Since the weights provided in the NCES surveys are designed to provide a nationally-representative sample, they may not be suited for analyses at the state level. To remedy this issue, for our state-level analysis, we construct state-based weights which are intended to be more representative of state compositions. We base these weights on the closest decennial Census to the NCES survey in question: i.e. 1980, 1990, and 2000 for the HSB, NELS and ELS respectively. For each Census year, we restrict the sample to heads of households and their spouses (if present in household) reporting a child of high school age (15 to 18 years). We then generate frequency weights by state based on the following parental characteristics: single/two-parent household, maximum education of parents, race of head of household.

Supplementary Tables

Table A1: Marginal Distribution of Parent and Child Education

	HSB (1982)			NELS (1992)			ELS (2004)		
	Level	Years	Percentage	Level	Years	Percentage	Level	Years	Percentage
Parent	Dropout	10	25.12	LT 8th Grade	6	6.11	Dropout	10	13.35
				Some HS	10.5	8.58			
	HSG	12	30.7	GED	12	2.55	HSG/GED	12	28.25
				HSG	12	18.46			
	Voc, LT 2 yrs	13	3.69	Voc, LT 1 yr	12.5	3.45	Post sec, LT 2 yrs	13	9.4
				Voc, 1-2 yr	13.5	4.56			
	Voc, 2+ yr	14	5.98	Voc, 2+ yr	14	3.98			
	Coll, LT 2 yr	13	5.39	Coll, LT 2 yr	13	10.67	AA	13	7.8
	Coll, 2+ yr	14	6.55	Coll, 2+ yr	14	8.89	Coll, no grad	14	9.27
				AA	14	3.41			
	Coll Grad	16	12.01	Coll Grad	16	14.69	Coll Grad	16	17.89
	Master's	18	5.86	Master's	18	8.23	Master's	18	8.38
	PhD	21	4.69	PhD	21	6.42	PhD	21	5.65
Num. Categories	9			13			8		
Child	Dropout	11	5.62	Grade 9	9		Dropout	11	1.79
				Grade 10	10				
				Grade 11	11				
				Grade 12	12	4.85			
	HSG	12	50.80	HSG	12	16.93	HS, no PS	12	9.53
				Post HS	13	29.59	PS attendance	13	29.59
	License/Cert	13	4.96	License	13	7.91	Undergrad Cert	13	8.81
	AA	14	6.70	AA	14	7.26	AA	14	8.47
	Coll Grad	16	22.61	BA	16	29.56	BA	16	31.79
	Some Postgrad	17	4.45				Post-bacc	17	0.99
	MA/Professional	18	4.73	Master's	18	3.24	Master's	18	6.74
	PhD	21	0.14	PhD	21	0.62	PhD	21	2.30
Num. Categories	7			11			9		
Survey Year - Grade 12 Year	10			8			8		
Total observations	8670			9563			11711		

Total observations calculated under following sample restrictions: both parents in household, both parents' have non-missing education.

Table A2: Education Intergenerational Regression Coefficients - Varying Parent/Child

		Years Education			Years (standardized)			Education Percentile			Truncated Normal		
		1982	1992	2004	1982	1992	2004	1982	1992	2004	1982	1992	2004
Father	Son	0.272	0.201	0.269	0.384	0.227	0.366	0.354	0.446	0.363	0.363	0.458	0.373
s.e.		(0.017)	(0.047)	(0.016)	(0.024)	(0.055)	(0.021)	(0.017)	(0.022)	(0.016)	(0.014)	(0.032)	(0.017)
N			10820			10820			10820			10820	
Father	Daughter	0.294	0.257	0.261	0.415	0.335	0.351	0.367	0.431	0.342	0.375	0.456	0.348
s.e.		(0.014)	(0.026)	(0.014)	(0.020)	(0.035)	(0.018)	(0.015)	(0.026)	(0.018)	(0.017)	(0.026)	(0.019)
N			11380			11380			11380			11380	
Mother	Son	0.282	0.230	0.260	0.316	0.203	0.301	0.294	0.406	0.309	0.295	0.435	0.312
s.e.		(0.022)	(0.057)	(0.017)	(0.025)	(0.051)	(0.019)	(0.014)	(0.027)	(0.018)	(0.015)	(0.024)	(0.015)
N			13450			13450			13450			13450	
Mother	Daughter	0.320	0.306	0.285	0.358	0.313	0.326	0.348	0.411	0.308	0.354	0.437	0.320
s.e.		(0.017)	(0.033)	(0.014)	(0.019)	(0.034)	(0.016)	(0.016)	(0.029)	(0.017)	(0.014)	(0.027)	(0.017)
N			15290			15290			15290			15290	

Notes:
Column headings denote categorization of education variable used in intergenerational regression.
Education Percentile = [(number with strictly less education) + 0.5(number with equal education)]/(total number).
Truncated Normal: conditional expectation of latent continuous variable, based on observed education category, and assuming latent variable takes standard normal distribution.
Sample: all families where specified parent is in household, with non-missing education.
Observations weighted for national representation. Displayed number of observations rounded to nearest 10.
Controls: child race, state fixed effect.
Standard errors generated by bootstrap.

Table A3: Education Intergenerational Regression Coefficients - Varying Sample/Weights

	Baseline Sample & Weight	+ 2 Parents in HH	+ 2 Parent Edu. Nonmiss.	Baseline Sample, unweighted
1982	0.354	0.371	0.387	0.347
	(0.010)	(0.010)	(0.010)	(0.008)
1992	0.463	0.464	0.461	0.431
	(0.015)	(0.024)	(0.023)	(0.008)
2004	0.325	0.350	0.350	0.332
	(0.010)	(0.013)	(0.012)	(0.009)
p-value: 1982 = 1992?	0.000	0.001	0.001	0.000
p-value: 1992 = 2004?	0.000	0.000	0.000	0.000
p-value: 1982 = 2004?	0.068	0.234	0.009	0.205
N	30720	21470	20220	30770

Notes:
Displayed coefficients from intergenerational regression of education percentiles.
Education Percentile = [(number with strictly less education) + 0.5(number with equal education)]/(total number).
Parent education measured by maximum of both parents.
Baseline sample: children of both genders, with non-missing education and at least one parent with non-missing education.
Baseline: observations weighted for national representation using survey weights. Displayed number of observations rounded to nearest 10.
Controls: child race, child gender, state fixed effect.
Standard errors generated by bootstrap.

Table A4: Education Intergenerational Regression Coefficients - Varying Categorization of Education

	Education Percentile	Completed Degrees	+ GED = HSG
1982	0.354	0.352	0.343
	(0.010)	(0.010)	(0.011)
1992	0.463	0.426	0.410
	(0.015)	(0.016)	(0.016)
2004	0.325	0.295	0.294
	(0.010)	(0.010)	(0.009)
p-value: 1982 = 1992?	0.000	0.000	0.000
p-value: 1992 = 2004?	0.000	0.000	0.000
p-value: 1982 = 2004?	0.068	0.000	0.003
N	30720	30720	30720

Notes:
Displayed coefficients from intergenerational regression of education percentiles.
Education Percentile = [(number with strictly less education) + 0.5(number with equal education)]/(total number).
Parent education measured as maximum of both parents.
Sample: children of both genders, with non-missing education and at least one parent with non-missing education.
Observations weighted for national representation.Total observations rounded to nearest 10.
Controls: child race, child gender, state fixed effect.
Standard errors generated by bootstrap.

Table A5: Regression of Education Intergenerational Education Correlation Coefficients on State Income Inequality Measure

	Years	Education Percentile		Truncated Normal	Years	Education Percentile		Truncated Normal
Pooled Child Genders	-0.398	-0.329	-0.0435	-0.0116	0.616	0.835	1.202^{*}	1.302^{*}
	(0.279)	(0.335)	(0.299)	(0.298)	(0.396)	(0.523)	(0.564)	(0.527)
Observations	123	123	123	123	123	123	123	123
Sons	-0.731^{*}	-0.379	-0.0844	-0.120	0.687	0.856	1.122	1.125
	(0.300)	(0.474)	(0.450)	(0.469)	(0.589)	(0.884)	(0.958)	(0.876)
Observations	97	97	97	97	97	97	97	97
Daughters	-0.530	-0.147	0.131	0.233	0.215	1.071	1.374	1.466^{+}
	(0.429)	(0.449)	(0.419)	(0.406)	(0.721)	(0.750)	(0.832)	(0.803)
Observations	100	100	100	100	100	100	100	100
State FE	No	No	No	No	Yes	Yes	Yes	Yes
Marginal Distributions		National	State	State		National	State	State

Notes:
Each observation is a regression coefficient from a state x year specific intergenerational regression.
Columns differ by categorization of education used.
Parental education measured as maximum of both parents.
Education Percentile = [(number with strictly less education) + 0.5(number with equal education)] / (total number)
Education percentiles calculated child position in national distribution, and alternatively in state distribution.
Truncated Normal: conditional expectation of latent continuous variable, based on observed education category, and assuming latent variable takes standard normal distribution.
Rows display results from different child samples: pooled and separate by gender.
State income inequality measure: gini coefficient.

Table A6: Regression of Intergenerational Correlation Coefficients (Income on Education, State Level)

	Years Attained		Education Percentile		Truncated Normal	
	All Classes	2004	All Classes	2004	All Classes	2004
IG Correlation, Education	0.358**	0.482**	0.210**	0.265+	0.225**	0.310*
	(0.0935)	(0.161)	(0.0754)	(0.150)	(0.0703)	(0.126)
Mean (S.D.), Education Coefficient	0.25 (0.20)		0.36 (0.10)		0.35 (0.10)	
Mean (S.D.), Income Coefficient	0.27 (0.04)					
Survey Year Fixed Effect	Yes	No	Yes	No	Yes	No
Observations	122	42	122	42	122	42

Notes:
Each observation is one state x survey year.
Dependent variable: Income rank-rank slope, measured from 1986 birth cohort.
Column headings show empirical method used for estimating intergenerational correlation.
All Classes: Regression sample contains high school graduating classes of 1982, 1992, 2004.
2004: Regression sample only contains high school graduating class of 2004.
Education Percentile = [(number with strictly less education) + 0.5(number with equal education)] / (total number).
Truncated Normal: conditional expectation of latent continuous variable, based on observed education category, and assuming latent variable takes standard normal distribution.
In intergenerational regression for education, children of both genders included.
Parental education: maximum of both parents.
In secondary regression, education coefficients weighted inversely by standard error.

Table A7: Parent - Child Mobility Matrices by Survey Year

	HSB (1984)			
	Dropout	High School Degree	Some Post-secondary	College Degree
Dropout	16.74	67.97	7.664	7.626
High School Degree	7.719	65.82	10.90	15.56
Some Post-secondary	4.395	57.30	11.77	26.53
College Degree	1.922	36.16	8.867	53.05
	NELS (1992)			
	Dropout	High School Degree	Some Post-secondary	College Degree
Dropout	14.10	29.26	50.82	5.819
High School Degree	7.113	31.17	45.70	16.01
Some Post-secondary	2.528	18.10	53.63	25.74
College Degree	0.346	3.138	34.48	62.04
	ELS (2004)			
	Dropout	High School Degree	Some Post-secondary	College Degree
Dropout	14.57	20.80	54.07	10.57
High School Degree	6.936	21.74	52.83	18.49
Some Post-secondary	3.583	13.67	57.12	25.62
College Degree	2.049	5.435	40.42	52.10

Notes:
Parental education: maximum of both parents.
Sample: children of both genders, with non-missing education for self and at least one parent.
Observations weighted for national representation.

Table A8: Matrix-based Summary Measures of Mobility

M_1	$\frac{m-\sum_i p_{ii}}{m-1}$
M_2	2nd largest eigenvalue
M_3	$\lvert \det(P) \rvert$
M_4	$\frac{m-m\sum_i \pi_i p_{ii}}{m-1}$
M_5	$\frac{\sum_i \sum_j \pi_i p_{ij} \lvert i-j \rvert}{m-1}$

Table A9: Minimum Quantile of Parent/Child Human Capital for Attaining Each Level of Education

	Years of Education			
	8	12	14	16
Time Period 1				
Parent	0	15	50	75
Child	0	7	65	75
Time Period 2				
Parent	0	5	25	59
Child	0	7	17	65

Table A10: Marginal Distribution of Parents' Education - NCES vs. Census

Father

	NCES 1982	NCES 1992	NCES 2004
Dropout	0.24	0.14	0.13
High School	0.31	0.22	0.29
Some Post-secondary	0.22	0.35	0.27
College	0.23	0.29	0.30
	Census 1982	**Census 1992**	**Census 2004**
Dropout	0.27	0.16	0.13
High School	0.36	0.33	0.40
Some Post-secondary	0.17	0.27	0.21
College	0.21	0.24	0.26

Mother

	NCES 1982	NCES 1992	NCES 2004
Dropout	0.20	0.14	0.13
High School	0.43	0.29	0.27
Some Post-secondary	0.22	0.40	0.35
College	0.15	0.17	0.25
	Census 1982	**Census 1992**	**Census 2004**
Dropout	0.27	0.16	0.13
High School	0.45	0.39	0.42
Some Post-secondary	0.17	0.28	0.23
College	0.11	0.17	0.22

Supplementary Figures

Figure A1: Standardized Reading Scores by Years of Education (NCES Children)

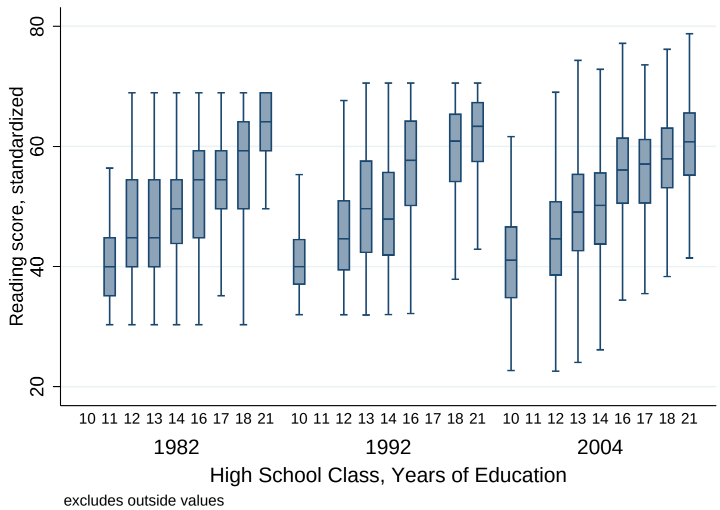
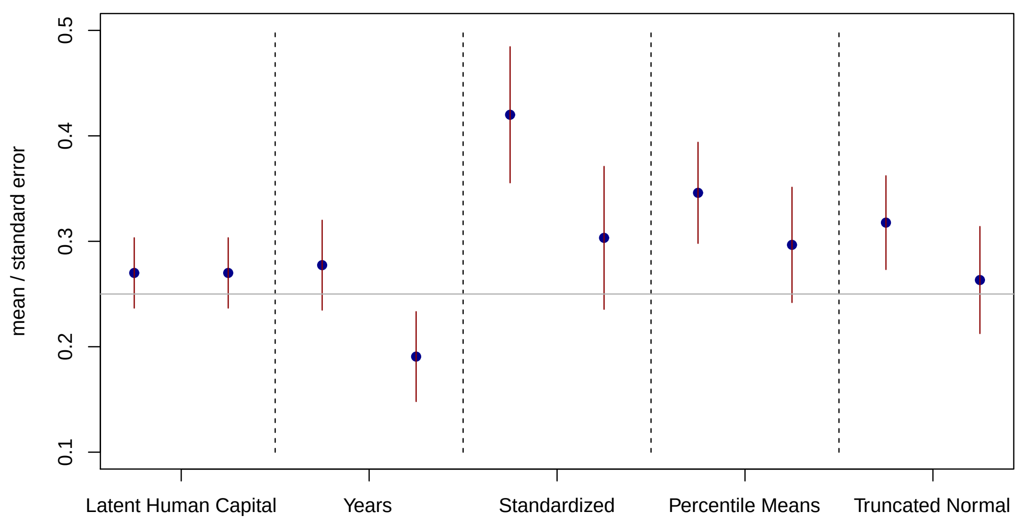
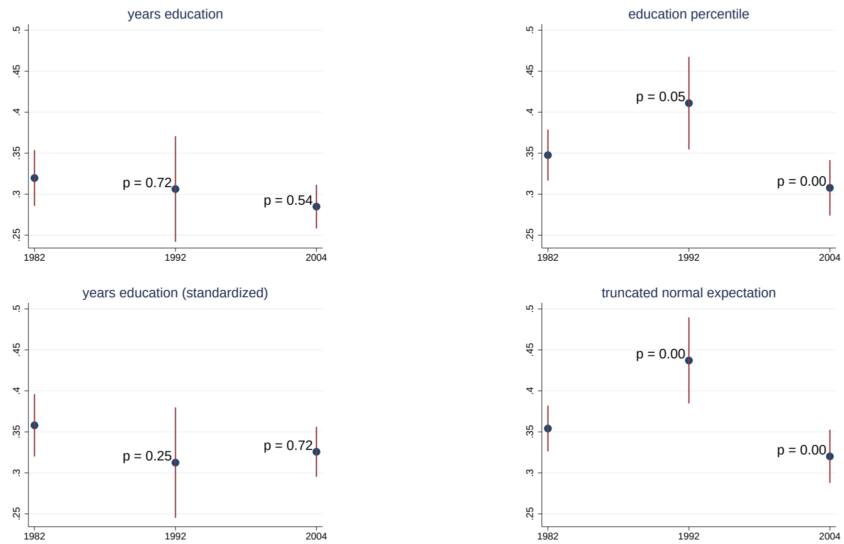


Figure A2: Estimates of Intergenerational Correlations in Education, Using Different Empirical Approaches



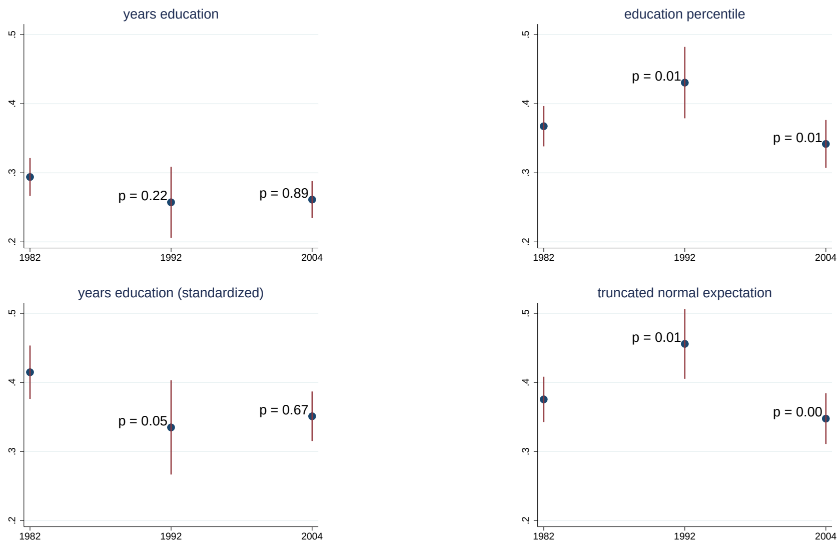
For each empirical approach, Left and Right points represent intergenerational correlation estimate under Time Period 1 and 2, respectively. Time periods differ in mapping between human capital and education level (A9). Horizontal line denotes true value of intergenerational correlation parameter (0.25) in each time period.
Bars show standard errors.

Figure A3: Education IG Correlation Coefficients over Time (Mother-Daughter)



Graph titles indicate education variable used in intergenerational regression.
Education Percentile = [(number with strictly less education) + 0.5(number with equal education)]/(total numbe
Truncated Normal Expectation: expectation of latent continuous variable, conditional on observed education ca
Observations weighted for national representation. Parental education measured from mother..
Sample: all families where specified parent is in household, with non−missing education. Sample restricted to
Controls: child race, state fixed effect.
95% confidence intervals shown.
P−value of test for equality, between this survey year and previous survey year.

Figure A4: Education IG Correlation Coefficients over Time (Father-Daughter)



Graph titles indicate education variable used in intergenerational regression.
Education Percentile = [(number with strictly less education) + 0.5(number with equal education)]/(total numbe
Truncated Normal Expectation: expectation of latent continuous variable, conditional on observed education ca
Observations weighted for national representation. Parental education measured from father..
Sample: all families where specified parent is in household, with non−missing education. Sample restricted to
Controls: child race, state fixed effect.
95% confidence intervals shown.
P−value of test for equality, between this survey year and previous survey year.

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