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Abstract

Research on intergenerational mobility has often treated outcomes such as schooling and earnings as being imperfectly transmitted from one parent to a child. But because the characteristics of both parents are important in shaping children's outcomes, the way in which a generation of parents is sorted into couples is likely to be a key determinant of intergenerational persistence. Mating patterns are assortative—that is, individuals tend to partner with people similar to themselves—and this is typically measured by similarity of educational attainment. I present the first estimates of the effect of assortative mating on intergenerational persistence of schooling and earnings. I measure assortative mating as the rank correlation of couples' educational attainment, that is, the degree to which the most highly-educated men partner with the most highly-educated women. Using data on parents and children in the United States, I find that assortative mating explains about one quarter of the observed intergenerational persistence of schooling and earnings.

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1 Introduction

The question of why there is strong intergenerational persistence of schooling and earnings is crucial for determining the degree to which intergenerational persistence might be responsive to policy changes, and whether such policies are desirable. Much of the literature on intergenerational persistence has treated a family as having one parent. But because the characteristics—including financial resources, genetics, attitudes, etc.—of *both* parents influence a child's outcomes, the way in which a group of parents is sorted into couples is likely to be important in determining the degree of intergenerational persistence.

This paper studies the effect of educational assortative mating—the tendency of individuals to marry people with educational attainment similar to their own—on intergenerational persistence of schooling and earnings in the United States. Using a statistical model consistent with canonical optimizing models of intergenerational persistence, I show that more highly assortative mating will increase the degree to which a parent's schooling or earnings persist to a child. In data on parents and children from the PSID, I show that assortative mating can explain about one quarter of the observed intergenerational persistence of schooling and earnings.

The simplest way in which assortative mating affects intergenerational persistence is through a mechanical or statistical effect. Consider measuring the degree of persistence in educational attainment from fathers to sons. Suppose that parents' educational attainment is determined before the couple has children, and that both father's education and mother's education have positive effects on the child's educational attainment. If highly educated fathers mate with highly educated mothers, then the effect of mother's education on the child's education reinforces the effect of father's education, and the correlation between father's education and son's education will be high. On the other hand, if highly educated fathers mate with mothers having low levels of education (a situation known as negatively assortative, or disassortative, mating), then the effect of the mother's low education is to bring the child's educational attainment closer to the mean, so the correlation between father's education and son's education will be lower. The statistical model in section 2 makes this point analytically.

Another important way in which assortative mating affects intergenerational persistence is through the labor supply decisions of parents. These labor supply decisions will affect the family's income and the financial resources available to the parents for investment in their children's human capital. In the household labor supply model of Bredemeier and Juessen (2013), couples face a specialization decision over market work and household production. The wife's hours worked are increasing in her wage relative to her husband's wage. If couples are randomly matched, relative wages are lowest for wives of high-earning husbands, so these wives work least, and the distribution of family income is more compressed than the distribution of husbands' earnings. This mitigates intergenerational persistence between fathers and children. On the other hand, if couples are perfectly matched, then wives of high-earning husbands work about as much as wives of low-earnings husbands, and intergenerational persistence from fathers to children is not lessened by the pattern of wives' labor supply.

I measure educational assortative mating as the degree of rank correlation between parents' education levels. That is, mating is perfectly assortative when the most highly-educated men partner with the most highly-educated women, and the least-educated men partner with the least-educated women. I use Census data to convert the number of years of education of each parent in my sample to the parent's percentile rank within the education distribution specific to their sex and birth cohort. I then create an assortativity measure based on parents' difference in percentile ranks. If mating were perfectly assortative on education, then in each couple both parents would have the same percentile rank, so my assortativity measure would be zero for each couple. As mating becomes less assortative, the average rank distances within couples increase, and my assortativity measure becomes more negative.

This method of measuring educational assortative mating is a departure from most previous research. Sociological literature tends to focus on the incidence of homogamy—marriage between two people having the same number of years of education—and heterogamy—marriage in which the partners' educational attainment differs (Schwartz and Mare, 2005). However, these measures may be changed over time by differential trends in sex-specific education distributions.

For example, suppose it were always the case that marriage was highly assortative with respect to education, in the sense that the most-educated men tended to marry the most-educated women. In times when average educational attainment was lower among women than men, then this would produce many couples with heterogamous marriages, in which the husband had more education than the wife. If the education distributions of men and women then became very similar, the incidence of homogamy, in which partners share the same level education, would increase, even with no underlying changes in behaviors in the marriage market.

More generally, my conception of assortative mating as based on the correlation of partners' education ranks reflects the fact that education is in part a proxy for unobserved characteristics—often referred to collectively as "endowments" in the literature on intergenerational persistence—such as cognitive ability and non-cognitive skills. These unobserved characteristics are important both for sorting patterns among a generation of parents and for how parents' economic outcomes are transmitted to children. The sex-specific distributions of these characteristics are likely to be much more similar than are the sex-specific distributions of education. Therefore, using percentile ranks from sex-specific education distributions to measure assortativity will reflect both patterns of assortative mating on education, as well as unobserved assortative mating on important characteristics that are correlated with educational attainment.

In research on intergenerational transmission of education and earnings, the most common measure of persistence is the slope coefficient from a simple regression of a child's outcome on a parent's outcome. My measure of the effect of assortative mating on intergenerational persistence is the degree to which this slope coefficient is larger in families with higher assortativity. I regress the child's outcome on a parent's outcome, parents' assortativity, and an interaction between the parent's outcome and assortativity. If higher assortativity is correlated with stronger intergenerational transmission of schooling or earnings, then the coefficient on the interaction term will be positive.

A major challenge in interpreting the resulting estimates, of course, is that assortativity is not randomly assigned. Suppose there is a group of parents with an especially strong preference for their children's outcomes. This can cause intergenerational persistence to be higher among this group, for two distinct reasons. First, the strong preference for children's outcomes may lead them to place more importance on partnering with the best available mate, which increases assortative mating among the group. This raises intergenerational persistence among the group, for the reasons explained above, and this is the effect I would like to measure. Second, in the canonical model of intergenerational transmission with one-parent families (Becker and Tomes, 1979), the share of the parent's wealth that is invested in the child's human capital is increasing in the parent's taste for the child's future earnings. Therefore, in this hypothetical group of parents, intergenerational persistence would be higher, even before mating patterns are considered.

To address this, I use control variables that are plausibly correlated with preferences and are predetermined with respect to the parents' mating decisions. These controls include the parents' birth cohort, birth region, race, and education. The controls cannot be directly entered into the regression of child's outcome on parent's outcome. Doing so would mean that the coefficient on parent's outcome represents a partial effect, conditional on controls, rather than a total effect. Instead, I first purge the assortativity measure of the control variables in a first-step regression. The residuals from the first-step regression are by construction uncorrelated with the controls. The second step is a regression of child's outcome on parent's outcome, assortativity residuals from the first step, and an interaction between parent's outcome and assortativity residuals.

I find that assortativity is positively correlated with intergenerational persistence. These results are more often statistically significant, and more stable as control variables are added, for schooling persistence than for earnings persistence. To estimate the overall effect of assortativity on intergenerational persistence, I use the regression results to compare intergenerational persistence at the observed average level of assortativity to the degree of persistence that is predicted to prevail if couples were matched randomly. For both schooling and earnings, I find that assortative mating explains about one quarter of the observed level of intergenerational persistence.

A large literature studies the level and causes of intergenerational transmission of schooling and earnings. See Solon (1999) and Black and Devereux (2011) for reviews. The model of Becker and Tomes (1979) shows that the degree of persistence reflects both the heritability of productive endowments and the fact that wealthier parents invest more in their children's human capital. Becker (1991) notes that more assortative mating among the parent generation will increase heritability of endowments and thus intergenerational earnings persistence. This paper presents the first empirical evidence on the magnitude of this effect.

Although previous research has not focused on the effects of assortative mating among the parents' generation, some research has used differences in family types to learn about the process of intergenerational persistence. For example, Björklund, Lindahl, and Plug (2006) and Liu and Zeng (2009) analyze differences in persistence between adoptees and children raised with their biological parents. Under some assumptions, this is informative about the relative importance of pre-birth and post-birth factors. Chetty et al. (2014) show that earnings persistence is lower in geographic areas of the U.S. where rates of single parenthood are higher.

A small previous literature, including Chadwick and Solon (2002), Ermisch, Francesconi, and Siedler (2006), and Holmlund (2008), has studied a separate role in intergenerational persistence of assortative mating among the *offspring* generation: a child's choice of partner mechanically affects how similar the child's family income is to the family income of the child's parents.

There is also a literature that studies the effect of marital sorting on inequality of household income within a generation. If marriage is perfectly assortative, the variance of household income will be higher than if couples were formed through random mating. Recent studies of the magnitude of this phenomenon include Schwartz (2010), Eika, Mogstad, and Zafar (2014), Greenwood et al. (2014) and Pestel (2014). Along similar lines, Kremer (1997) and Fernández and Rogerson (2001) use dynamic models, calibrated to U.S. data, to study the effect of a permanent increase in assortative mating on steady-state inequality.

The remainder of the paper is organized as follows. The statistical model in section 2 shows how assortative mating increases intergenerational persistence. Section 3 discusses the data sources, and section 4 is about my measure of assortative mating. Section 5 details the empirical strategy, the results of which are presented in section 6. Section 7 concludes.

2 Statistical model

In this section I use a simple statistical model of intergenerational transmission to clarify how assortative mating affects intergenerational persistence of human capital and earnings. The model extends the framework of Lefgren, Lindquist, and Sims (2012) to families with two parents and is consistent with the canonical model of Becker and Tomes (1979) showing how intergenerational transmission arises from optimizing behavior. Higher assortativity increases intergenerational persistence of human capital and earnings, and increases the variance of human capital and earnings among the offspring generation. In the introduction, I discussed how assortative mating may affect intergenerational persistence both mechanically and through changes in parents' labor supply decisions. The statistical model captures the first effect only, and does not attempt to model household labor supply.

Each family consists of two parents, named f and m, and a child, c. The earnings of each family member depend on human capital and market luck. Human capital, h, includes education and genetic endowments, denominated in dollar equivalents. Market luck, ν, is assumed to be uncorrelated with each family member's human capital and with other family members' market luck. The earnings equations are

$$\begin{aligned} Y^f &= \mu + h^f + \nu^f; \\ Y^m &= \mu + h^m + \nu^m; \\ Y^c &= \mu + h^c + \nu^c. \end{aligned} \tag{1}$$

One contribution of Becker and Tomes (1979) was to show that parents increase their children's human capital and earnings in two major ways. First, higher-income parents are able to invest more in their children's human capital.

Second, higher-income parents tend to have more favorable genetic endowments—here, reflected in higher human capital—which are passed on to their children through genetic and cultural inheritance. The equation describing production of children's human capital captures this insight:

$$h^c = \lambda + \pi_Y(Y^f + Y^m) + \pi_h(h^f + h^m) + \phi^c, \tag{2}$$

where $\pi_Y > 0$ is parents' propensity to invest financial resources in the child's human capital, $\pi_h > 0$ is heritability of human capital, and ϕ^c is white noise.

Substituting this into the child's earnings equation, (1), yields the classic result on intergenerational earnings transmission first described in Becker and Tomes (1979):

$$Y^c = (\lambda + \mu) + \pi_Y(Y^f + Y^m) + \pi_h(h^f + h^m) + \phi^c + \nu^c. \tag{3}$$

Suppose that there is assortative mating on human capital. Becker (1991) modeled assortative mating on both endowments and earnings, but assortativity on human capital alone is plausible if matching occurs before labor market entry or early enough in a career that values of market luck are not yet known. The linear sorting equation that describes how parents match is

$$h^m = \bar{h}(1 - r) + rh^f + \psi, \tag{4}$$

where $\bar{h}$ is average human capital, r is the correlation between parents' human capital, and the stochastic element ψ is assumed to be uncorrelated with h^f.

To see how assortative mating affects intergenerational transmission, first consider the most common measure of human capital persistence: the slope coefficient in a simple regression of child's human capital, h^c, on father's human capital, h^f. By substituting the earnings equations, (1), into the human capital equation, (2), then using the sorting equation, (4), the slope estimator in the simple regression converges to

$$\text{plim } \hat{\beta}_{h^c,h^f} = (1 + r)(\pi_Y + \pi_h). \tag{5}$$

As assortativity, r, increases, intergenerational transmission of human capital also increases.

Similarly, assortativity increases intergenerational transmission of earnings. Consider a simple regression of child's earnings, Y^c, on father's earnings, Y^f. By substituting the earnings equations, (1), into the earnings transmission equation, (3), then using the sorting equation, (4), the slope estimator in the regression converges to

$$\text{plim } \hat{\beta}_{Y^c,Y^f} = (1+r)(\pi_Y + \pi_h)\frac{\text{Var}(h^f)}{\text{Var}(Y^f)} + \pi_Y \frac{\text{Var}(\nu^f)}{\text{Var}(Y^f)}. \tag{6}$$

This measure of earnings persistence is increasing in assortativity, r.

Note that the magnitude of the effect of assortativity is larger for earnings persistence in equation (6) than for human capital persistence in equation (5). This is due to the child's market luck, which generates regression to the mean because it is realized after the parents' investments in the child's human capital have been made. For the same reason, estimates of the effect of assortativity will be noisier for earnings persistence than for schooling persistence. The standard errors of the regression coefficients are increasing in the variance of the disturbance in the model, and the child's market luck increases the residual variance of earnings relative to the residual variance of human capital.

Assortative mating also has a mechanical effect of increasing the inequality of family income among parents. If men and women with high education and earnings potential tend to marry, then the variance of family income will be higher than if couples were formed randomly. This has been studied recently by Schwartz (2010), Eika, Mogstad, and Zafar (2014), and Greenwood et al. (2014). Using the earnings equation, (1), and the sorting equation, (4), the variance of parents' family income is

$$\text{Var}(Y^f + Y^m) = (1+r)^2\text{Var}(h^f) + \text{Var}(\psi) + \text{Var}(\nu^f) + \text{Var}(\nu^m), \tag{7}$$

which is increasing in assortativity among parents, r.

Some of this increased inequality will persist in the children's generation, although regression to the mean will eliminate part of it. The variance of earnings among children is

$$\begin{aligned} \text{Var}(Y^c) = (1+r)^2(\pi_Y + \pi_h)^2\text{Var}(h^f) + (\pi_Y + \pi_h)^2\text{Var}(\psi) \\ + \pi_Y^2\big(\text{Var}(\nu^f) + \text{Var}(\nu^m)\big) + \text{Var}(\phi^c) + \text{Var}(v^c). \end{aligned} \tag{8}$$

3 Data

The sample of children and parents comes from the Panel Study of Income Dynamics (PSID), which began with a random sample of about 5,000 U.S. households in 1968. This sample was reinterviewed annually through 1997, and every two years thereafter. Each round of the survey collects data on a wide range of variables, including income from the previous calendar year. Children in the original sample have been followed as they grow older and form their own households, making the PSID a very common data source for studies of intergenerational transmission of social and economic outcomes.

In constructing my sample, I first exclude the Survey of Economic Opportunity component of the sample (sometimes called the poverty sample) because of strong concerns about the sample's selection (Brown, 1996). I require that the child and both biological parents be observed at least once beginning at age 25, so that reported schooling is likely to reflect final educational attainment. Children whose parents were both in the survey at any time, and have a valid schooling observation, will be included in my sample regardless of whether the parents were married at the time of observation, and regardless of what happened to the parents' relationship in the future. If it is not the case that both of the child's biological parents were observed—whether because the parents were separated when the survey began, or one of the parents had died, etc.—then the child is not in my sample. I also exclude children born before 1952, who were older than 16 when the survey began in 1968, to avoid over-representing children who remained at home longer. These restrictions yield a sample of 1,780 sons and 1,810 daughters that are included in the results on schooling persistence.

Further restrictions are necessary for the earnings persistence sample. I drop outlier earnings observations below $100 or above $150,000 in 1967 dollars, then purge the remaining log earnings values of year effects. In a regression of child's log earnings on a parent's log earnings, the year-to-year transitory variation in the parent's log earnings means that a single year's observation of the parent's log earnings is a noisy estimate of the parent's permanent log earnings. If this transitory component of earnings is classical, there is attenuation bias in the estimate of intergenerational earnings persistence (Solon, 1992). To address this, I follow previous research on earnings persistence by estimating the parent's permanent log earnings using a multi-year average of the parent's annual log earnings. In particular, I require that the parent's earnings be observed five times between ages 25 and 59. If more observations are available, I use the five observations closest to age 40, as this is when annual log earnings are the best estimate of lifetime permanent log earnings (Haider and Solon, 2006). Few mothers in my sample have at least five earnings observations, so I examine only father-child earnings persistence. These restrictions leave a sample of 1,052 sons and 1,019 daughters to be used in the results on earnings persistence.

My measure of assortative mating, which is discussed in more detail in section 4, is based on the similarity of parents' percentile ranks within cohort-by-sex-specific distributions of educational attainment. The PSID is far too small to estimate these distributions with any precision. Instead, I use the IPUMS 1940–2000 decennial Census files and the 2008–2012 ACS five-year file (Ruggles et al., 2010) to estimate distributions of educational attainment at the cohort-by-sex level. Each survey year is used to find the education distributions for cohorts who were ages 35–44 at the time of the survey, which gives sex-specific education distributions for birth cohorts from 1896 to 1977. The oldest parent in my sample was born in 1902, and the youngest was born in 1970.

4 Measure of assortative mating

To exploit variation across families in the degree of assortative mating, I use a family-specific measure of assortativity. Previous literature overwhelmingly uses years of educational attainment to measure the degree of assortative mating, so one natural family-level measure of assortativity would be some function of the difference between the parents' levels of educational attainment. However, the distribution of education attainment differs between males and females, and these differences have themselves changed over time (Acemoglu and Autor, 2011). As a result, a function of the difference between the parents' levels of education would be hard to interpret, and the distribution might drift across birth cohorts as education distributions changed, without any underlying change in the pattern of assortativity as defined by the rank correlation of couples' education. This point has been made independently, and solved differently, by Eika, Mogstad, and Zafar (2014).

To measure assortative mating, then, I begin not with individual education levels but with education ranks. Mating is perfectly assortative when the most highly-educated men marry the most highly-educated women, so that ranks within sex-specific education distributions are the same for both partners in a couple. As the degree of assortativity decreases, the average difference in couples' percentile ranks increases. I use Census data to compute cohort-by-sex-specific education distributions, then convert each PSID respondent's reported level of education, s, to their percentile rank within the appropriate education distribution, k.

My family-specific measure of assortative mating is the negative of the squared difference in the parents' educational ranks:

$$r_i = -(k_i^f - k_i^m)^2. \tag{9}$$

This index is constructed so that smaller negative values represent more assortativity, up to a maximum of zero when the parents' ranks within their respective education distributions are the same. The index is not affected by by sex differences in education distributions or by changes over time in education distributions. The Spearman rank correlation coefficient, ρ, is linearly related to the cross-family mean of the assortativity index: $\rho \approx 1 + 6\bar{r}$.

Table 1 summarizes the degree of parents' assortativity among the children in the PSID who are eligible for the empirical analysis below. The table shows the mean of the parents' absolute difference in education ranks, $|k_i^f - k_i^m|$, and the mean of my assortativity measure, $r_i = -(k_i^f - k_i^m)^2$. On average for the children in my sample, parents' education ranks are about 16 percentiles apart, and $\bar{r} = -0.048$. There are only small differences in parents' assortativity between white and black children, and again only small differences across three categories of child's completed education. Parents' assortativity increased over time in this sample: the average difference in parents' education ranks was 16.4 percentiles among children born in the 1950s, and 13.6 percentiles among children born in the 1980s. This finding is consistent with Schwartz and Mare (2005), who find that the degree of assortative mating among new marriages was increasing from 1960–1995.

To give some context for these summary statistics, at the bottom of Table 1 I show the values of mean rank difference and mean assortativity under three different sorting patterns. The simplest case is perfectly assortative mating, in which each father is paired with a mother who has the same educational rank. There are no differences in education ranks, so $\bar{r} = 0$. If there is perfectly disassortative (or perfectly negatively assortative) mating, then each father is paired with a mother from the opposite position of the distribution of education ranks: the highest-educated male mates with the lowest-educated female, and so forth, so that $k_i^m = 1 - k_i^f$ for all i. In this case, one can show that the average rank distance is 50 percentiles, and that $\bar{r} = -\frac{1}{3}$. Finally, if matching is random, then the bivariate random variable (k_i^f, k_i^m) is uniformly distributed on the unit square. One can show that the average rank distance is 33 percentiles, and that $\bar{r} = -\frac{1}{6}$.[1] The observed level of assortativity, $\bar{r} = -0.048$, can be interpreted as showing that mating among parents is more than two thirds of the way toward perfectly assortative when compared to the case of random matching.

5 Empirical strategy

In this section I describe a two-step procedure for estimating the effect of assortativity on intergenerational persistence. While the procedure could be applied to persistence of many traits, for concreteness I discuss intergenerational persistence of earnings in this section. In section 6, I present results on persistence of both schooling and earnings.

By far the most common summary measure of intergenerational earnings persistence is the slope estimate from a simple regression in which the dependent variable is child's log earnings, y^c, and the explanatory variable is father's log earnings, y^f:

$$y_i^c = a_0 + a_1 y_i^f + e_{1i}. \tag{10}$$

[1] An additional advantage of my assortativity measure r_i, relative to using the absolute value of rank differences, is that in the case of random matching, $\bar{r}$ is exactly halfway between its value in the two extreme cases. This is not the case when rank distances are used.

Among developed countries, the estimated intergenerational earnings elasticity, $\hat{a}_1$, ranges from a high of between 0.4 and 0.5 in the U.S. and UK to a low of about 0.2 in Denmark, Finland, and Norway (Corak, 2013). One minus the intergenerational earnings elasticity is interpreted as a measure of intergenerational earnings mobility.

To study the effect of assortativity, r, controlling for some other variables, x, on intergenerational persistence, it is tempting to extend this approach by regressing child's log earnings on father's log earnings, assortativity, the controls, and interactions between father's log earnings and each of the other regressors, producing the regression

$$y_i^c = b_0 + b_1 y_i^f + b_2 r_i + x_i' b_3 + b_4 y_i^f r_i + y_i^f x_i' b_5 + e_{2i}, \tag{11}$$

where b_4 is the parameter of interest. However, this regression reveals how the *partial* effect of father's log earnings, controlling for the variables in x, varies with assortativity. This is not the question I am trying to answer, and moreover is difficult to interpret without some source of exogenous variation in father's log earnings.

Instead, I break up the estimation into two steps. In the first step, I regress assortativity, r, on control variables such as father's race and year of birth:

$$r_i = \alpha_0 + x_i' \alpha_1 + \varepsilon_{1i}. \tag{12}$$

The residuals from this regression, $\widetilde{r}$, are by construction uncorrelated with the control variables in x—that is, the assortativity residuals $\widetilde{r}$ have been purged of the controls. I then estimate the second step, a regression of child's log earnings on father's log earnings, the assortativity residuals, and the interaction of these residuals with father's log earnings:

$$y_i^c = \beta_0 + \beta_1 y_i^f + \beta_2 \widetilde{r}_i + \beta_3 \widetilde{r}_i y_i^f + \varepsilon_{2i}. \tag{13}$$

Then β_3 describes how the total effect of father's log earnings varies with differences in assortativity that are not explained by the control variables in x. If assortativity increases intergenerational earnings persistence, then $\beta_3 > 0$.

Other researchers have estimated the effects of regressors of interest on the intergenerational earnings elasticity, but all have used a single-equation approach similar to (11), rather than the two-step procedure in this paper. For example, Mayer and Lopoo (2008) study whether the intergenerational earnings elasticity in the U.S. varies with state government spending, conditional on state fixed effects, and Pekkarinen, Uusitalo, and Kerr (2009) estimate the effect of an education reform in Finland on the intergenerational earnings elasticity, conditional on child's region and cohort indicators. These papers, then, describe how the partial effect of father's earnings, conditional on the control variables, varies with the regressor of interest.

In the literature on measurement of the intergenerational earnings elasticity, researchers face two major estimation challenges associated with mismeasurement of child's and father's permanent log earnings. The first is that measurement error and transitory variation in father's log earnings, y_i^f, create attenuation bias in the estimated intergenerational earnings elasticity. This is commonly addressed by taking a multi-year average of parents' log earnings, which is the strategy I follow here. See section 3 for details.

The second estimation challenge is that yearly earnings is a downwardly biased measure of permanent earnings earlier in life, and an upwardly biased measure of permanent earnings later in life (Grawe, 2006). This form of measurement error is known as life cycle bias, and because it is non-classical, both error in the explanatory variable, father's permanent log earnings, and the dependent variable, child's permanent log earnings, may bias the estimated intergenerational earnings elasticity. The bias is smallest when earnings are measured around age 40, because this is the age at which annual earnings are the best estimate of lifetime permanent earnings (Haider and Solon, 2006). Therefore, one way to address the bias is to begin from the second-step regression (13) and add controls for a polynomial in father's age relative to 40 at the time of earnings measurement, $\text{age}_i^f - 40$, a polynomial in child's age relative to 40 at the time of earnings measurement, $\text{age}_i^c - 40$, and interactions between this latter polynomial and father's log earnings. Lee and Solon (2009) use a fourth-degree polynomial, and I follow that choice in this paper.

Because observations on educational attainment are taken after individuals are likely to have completed schooling, the schooling variables do not suffer from life cycle bias or, of course, transitory variation. Measurement error of schooling may occur, but is likely to be much less severe than for earnings.

6 Results

Tables 2–5 present results on the role of assortative mating in the intergenerational persistence of educational attainment, as measured by years of schooling. For each of the four intergenerational links—father-son, mother-son, father-daughter, and mother-daughter—there is strong evidence that higher assortativity among parents is associated with higher schooling persistence between parent and child. This effect of assortativity is larger for mother-child persistence than for father-child persistence.

In each table, the first column shows estimates of a simple regression of child's schooling on parent's schooling. An additional year of parent's schooling is associated with an increase of about 0.4 years in the child's schooling. In column 2, the second step regression, (13), is run without purging assortativity of any of the control variables. In each case, the interaction between assortativity and parent's schooling is positive and statistically significant at the one percent level, indicating that more assortativity among parents is associated with higher schooling persistence.

One way to estimate of the role of assortativity in intergenerational persistence is to compare schooling persistence at the observed mean value of assortativity, $\bar{r}_{\text{obs}}$, to predicted schooling persistence at the value of assortativity that would prevail if parents were randomly matched, $\bar{r}_{\text{random}}$. Because $\hat{\beta}_3$ is the estimated coefficient on the interaction of assortativity and parent's schooling, the difference in persistence between a regime of random matching and the observed sorting patterns is $\hat{\beta}_3(\bar{r}_{\text{obs}} - \bar{r}_{\text{random}})$. Recall from section 4 that if matching among parents is random, then the mean values of assortativity is $\bar{r}_{\text{random}} = -\frac{1}{6}$. The observed cross-family mean of assortativity varies slightly depending on the sample, but is always roughly $\bar{r}_{\text{obs}} = -0.05$.

In Table 2, the column 2 estimates indicate that intergenerational persistence of schooling is $0.68 \times (-0.05 - (-0.17)) = 0.08$ higher under observed parent sorting patterns than it would be if parents were matched randomly; this value is shown at the bottom of the column of regression estimates. This represents more than one fifth the observed father-son persistence of 0.36, reported in column 1. The estimated role of assortativity in father-daughter schooling persistence, shown in Table 3, is slightly larger. The results suggest that the observed levels of assortative mating, compared to random mating, increase schooling persistence by 0.10, which is about one quarter of the observed father-daughter persistence.

The role of assortativity in mother-child schooling persistence is even larger. Using the results in Table 4, column 2, mother-son schooling persistence is 0.16 higher than it would be under random matching, so assortative mating accounts for about 40 percent of the observed intergenerational persistence. According to the estimates in Table 5, column 2, mother-daughter schooling persistence is 0.13 higher than it would be under random matching, so assortative mating accounts for about one-quarter of the observed intergenerational persistence.

Of course, the results discussed so far should be viewed as providing descriptive evidence, rather than isolating the causal effect of assortativity on intergenerational persistence. The major issue is that closely-matched parents may differ from other parents in many ways that impact intergenerational transmission. As discussed in the introduction above, among parents with especially strong preferences for their children's outcomes, there are two reasons to expect higher intergenerational persistence. First, these parents may search harder for the best available mate, which will increase assortativity among the group. That, in turn, increases intergenerational persistence, and is the type of effect I want to measure. Second, even if sorting patterns were not different among this group of parents compared to the overall population, their strong preference for children's outcomes would still lead to higher intergenerational persistence. Part of the association between assortativity and intergenerational persistence, then, may be driven by this latter effect, which does not operate through sorting patterns among parents.

To the extent that there is important variation across marriage markets in preferences about children's outcomes, then one way to address this bias is to use variation in assortativity within marriage markets, rather than all variation. Therefore, I first control for interactions among birth decade, birth region, and race for each parent, because marriage markets are often roughly segmented along these lines. These demographic indicators are good controls because they are plausibly correlated with parents' preferences and are determined before the parents' mating decisions.

The R^2 from the first-step regression of assortativity on controls illustrates how much of the total variation in assortativity is not used in the second-step regression. Column 3 in Tables 2–5 shows that these demographic controls alone explain about 30 percent of the variation in assortativity. The assortativity residuals from this first step, then, use a subset of the total variation in assortativity that is noticeably different from the uncontrolled regressions in column 2.

After regressing assortativity on these demographic controls, the residuals from this first-step regression have been purged of correlation with the controls. The estimates of the second-step regressions in column 3 show that the demographic controls tend to increase the estimated effect of assortativity in producing father-child schooling persistence, and decrease the estimated effect of assortativity in producing mother-child schooling persistence. In all cases, the estimated effect of assortativity remains statistically significant.

Next, I add indicators for each parent's decile within their cohort-by-sex-specific education distribution, to address the concern that both assortativity and preferences may vary with parents' schooling. Column 4 in Tables 2–5 shows that the estimated role of assortativity in schooling persistence increases slightly compared to the more limited set of controls in column 3.

Tables 6 and 7 present the results on the role of assortative mating in father-son and father-daughter earnings persistence. (Few women in the sample of parents worked enough years to have a usable estimate of permanent earnings.) The first column shows estimates of a simple regression of child's log permanent earnings on parent's log permanent earnings. The estimated elasticity is 0.40 for father-son earnings persistence and 0.27 for father-daughter earnings persistence, consistent with previous literature.

The statistical model in section 2 predicts that the role of assortativity in earnings persistence will be smaller than its role in schooling persistence, because market luck adds variability to children's earnings; compare equations (2) and (3). For the same reason, estimates of the role of assortativity in earnings persistence are likely to be noisier than in the analysis of schooling persistence.

The estimates in column 2 of Tables 6 and 7 are consistent with this. I analyze the role of assortativity in earnings persistence using the same methods just discussed for schooling persistence. The estimated effects are positive, as expected, but smaller in magnitude and noisier compared to the results on schooling persistence. The observed sorting patterns among parents predict that the father-son and father-daughter earnings elasticities are 0.04 higher than would prevail under random matching.

As controls are added, the estimated effect of assortativity rises steadily for both father-son and father-daughter earnings persistence. Only for father-son persistence are the estimates sufficiently precise to be statistically significant. The controls explain a great deal of the variability across families in assortativity—over one third of the variation can be explained by the demographic controls alone, and almost half is explained when the education decile indicators are added. After the controls are added, assortative mating accounts for about one-quarter of the observed earnings persistence between fathers and either sons or daughters.

7 Conclusion

This paper provides the first empirical evidence on the effect of assortative mating on intergenerational persistence of schooling and earnings. I conceptualize educational assortative mating as the degree to which parents' percentile ranks within sex-specific education distributions are equally matched, that is, the degree to which the most-educated men partner with the most-educated women. This method is robust to sex differences in education distributions and to changes in those education distributions over time, and naturally reflects the fact that mating is likely to be assortative on many traits that are correlated with education. I also show how a two-step estimation method can be used to estimate the effect of a regressor of interest on intergenerational persistence.

I find than in the U.S., in families in which parents' education ranks are more closely matched, intergenerational persistence is higher. I use these results to predict levels of intergenerational persistence if mating were random instead of positively assortative. Observed patterns of assortative mating can explain about one quarter of intergenerational persistence of schooling and earnings.

It is interesting to consider whether these findings might have any implications for changes over time in intergenerational persistence or for understanding cross-country differences in intergenerational persistence. The summary statistics in Table 1 show that assortative mating among parents became stronger between the 1950s and 1980s in the U.S. Using the results in Table 6 on how assortativity affects earnings persistence between fathers and sons, the change in average assortativity over this time period predicts an increase in the intergenerational earnings elasticity of 0.016, which is small compared to the estimated elasticity of 0.40. Assortative mating can explain a significant fraction of the level of intergenerational persistence of schooling and earnings, but observed *changes* in assortativity over time do not predict large *changes* in intergenerational persistence.

The potential implications of these results for cross-country differences in persistence is less clear. It is well-documented that intergenerational earnings persistence is higher in the U.S. than in many other developed countries (Solon, 2002; Corak, 2013). But because the measure of assortativity in this paper is novel, it is unknown precisely how assortative mating in the U.S., as defined here, compares to assortativity in other countries. However, some research using other measures of assortative mating has shown that assortativity is higher in the U.S. than in many other developed countries (Fernández, Guner, and Knowles, 2005), notably including Britain, Canada, and the Nordic countries, for which the best comparative evidence exists showing that intergenerational earnings persistence is relatively high in the U.S. This raises the possibility, which may be an interesting direction for future research, that some of the difference in intergenerational persistence across countries may reflect differences in sorting patterns among parents.

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Table 1: Summary statistics on educational assortative mating

	Mean of rank distance $\lvert k_i^f - k_i^m \rvert$	Mean of assortativity $r_i = -(k_i^f - k_i^m)^2$
Overall	0.156	-0.048
By child's race:		
White	0.155	-0.047
Black	0.158	-0.051
Other	0.186	-0.071
By child's education:		
High school or less	0.158	-0.049
Some college	0.163	-0.050
College or more	0.150	-0.045
By child's decade of birth:		
1950s	0.164	-0.053
1960s	0.169	-0.054
1970s	0.153	-0.046
1980s	0.136	-0.037
1990s	0.151	-0.043
Alternative sorting patterns:		
Perfectly assortative	0	0
Random matching	0.333	-0.167
Perfectly disassortative	0.500	-0.333

Notes: $N = 4152$. For a child in family i, k_i^f is the father's percentile rank within the distribution of completed education among males born in the same year as the father, and k_i^m is the mother's percentile rank within the distribution of completed education among females born in the same year as the mother. The education distributions are estimated using decennial Census and ACS data. For precise definitions of the alternative sorting patterns, see section 4.

Table 2: Assortativity and father-son schooling persistence

	(1)	(2)	(3)	(4)
First step regression				
Dependent variable: parents' assortativity				
Constant		yes	yes	yes
Birth decade × birth region × race indicators for each parent			yes	yes
Education decile indicators for each parent				yes
R^2		0.00	0.30	0.37
Second step regression				
Dependent variable: child's schooling				
Assortativity residual × father's schooling		0.68^{***}	0.92^{***}	1.02^{***}
		(0.23)	(0.26)	(0.28)
Assortativity residual		-8.85^{***}	-12.11^{***}	-13.70^{***}
		(2.73)	(3.00)	(3.21)
Father's schooling	0.36^{***}	0.37^{***}	0.37^{***}	0.36^{***}
	(0.02)	(0.02)	(0.02)	(0.02)
Constant	9.12^{***}	8.98^{***}	9.00^{***}	9.11^{***}
	(0.22)	(0.22)	(0.22)	(0.22)
Estimated effect of assortativity		0.08	0.11	0.12

Notes: $N = 1780$. Estimated effect of assortativity refers to the difference between predicted persistence at the observed mean value of assortativity and predicted persistence at the value of assortativity that would prevail if parents were randomly matched; see text for details. Standard errors, in parentheses, are robust to heteroskedasticity and to clustering on PSID family ID. For tests of the null hypothesis that the regression parameter is zero, * indicates $p < 0.10$, ** indicates $p < 0.05$, and *** indicates $p < 0.01$.

Table 3: Assortativity and father-daughter schooling persistence

	(1)	(2)	(3)	(4)
First step regression				
Dependent variable: parents' assortativity				
Constant		yes	yes	yes
Birth decade $\times$ birth region $\times$ race indicators for each parent			yes	yes
Education decile indicators for each parent				yes
R^2		0.00	0.29	0.32
Second step regression				
Dependent variable: child's schooling				
Assortativity residual $\times$ father's schooling		0.81^{***}	0.93^{***}	0.93^{***}
		(0.21)	(0.25)	(0.26)
Assortativity residual		-10.21^{***}	-11.63^{***}	-11.48^{***}
		(2.47)	(3.09)	(3.17)
Father's schooling	0.39^{***}	0.39^{***}	0.39^{***}	0.39^{***}
	(0.02)	(0.02)	(0.02)	(0.02)
Constant	8.99^{***}	8.90^{***}	8.94^{***}	9.00^{***}
	(0.25)	(0.24)	(0.25)	(0.25)
Estimated effect of assortativity		0.10	0.11	0.11

Notes: $N = 1810$. Estimated effect of assortativity refers to the difference between predicted persistence at the observed mean value of assortativity and predicted persistence at the value of assortativity that would prevail if parents were randomly matched; see text for details. Standard errors, in parentheses, are robust to heteroskedasticity and to clustering on PSID family ID. For tests of the null hypothesis that the regression parameter is zero, * indicates $p < 0.10$, ** indicates $p < 0.05$, and *** indicates $p < 0.01$.

Table 4: Assortativity and mother-son schooling persistence

	(1)	(2)	(3)	(4)
First step regression				
Dependent variable: parents' assortativity				
Constant		yes	yes	yes
Birth decade × birth region × race indicators for each parent			yes	yes
Education decile indicators for each parent				yes
R^2		0.00	0.30	0.37
Second step regression				
Dependent variable: child's schooling				
Assortativity residual × mother's schooling		1.36^{***}	0.89^{**}	0.94^{***}
		(0.26)	(0.39)	(0.34)
Assortativity residual		-17.56^{***}	-12.02^{**}	-13.11^{***}
		(3.24)	(5.07)	(4.50)
Mother's schooling	0.41^{***}	0.40^{***}	0.40^{***}	0.41^{***}
	(0.02)	(0.02)	(0.02)	(0.02)
Constant	8.56^{***}	8.69^{***}	8.69^{***}	8.63^{***}
	(0.30)	(0.31)	(0.32)	(0.31)
Estimated effect of assortativity		0.16	0.10	0.11

Notes: $N = 1780$. Estimated effect of assortativity refers to the difference between predicted persistence at the observed mean value of assortativity and predicted persistence at the value of assortativity that would prevail if parents were randomly matched; see text for details. Standard errors, in parentheses, are robust to heteroskedasticity and to clustering on PSID family ID. For tests of the null hypothesis that the regression parameter is zero, * indicates $p < 0.10$, ** indicates $p < 0.05$, and *** indicates $p < 0.01$.

Table 5: Assortativity and mother-daughter schooling persistence

	(1)	(2)	(3)	(4)
First step regression				
Dependent variable: parents' assortativity				
Constant		yes	yes	yes
Birth decade × birth region × race indicators for each parent			yes	yes
Education decile indicators for each parent				yes
R^2		0.00	0.29	0.32
Second step regression				
Dependent variable: child's schooling				
Assortativity residual × mother's schooling		1.07^{***}	0.55^{*}	0.63^{**}
		(0.27)	(0.30)	(0.27)
Assortativity residual		-13.70^{***}	-6.97^{*}	-8.20^{**}
		(3.62)	(4.13)	(3.75)
Mother's schooling	0.47^{***}	0.46^{***}	0.47^{***}	0.47^{***}
	(0.02)	(0.02)	(0.02)	(0.02)
Constant	8.03^{***}	8.10^{***}	8.07^{***}	8.05^{***}
	(0.29)	(0.29)	(0.30)	(0.30)
Estimated effect of assortativity		0.13	0.07	0.08

Notes: $N = 1810$. Estimated effect of assortativity refers to the difference between predicted persistence at the observed mean value of assortativity and predicted persistence at the value of assortativity that would prevail if parents were randomly matched; see text for details. Standard errors, in parentheses, are robust to heteroskedasticity and to clustering on PSID family ID. For tests of the null hypothesis that the regression parameter is zero, * indicates $p < 0.10$, ** indicates $p < 0.05$, and *** indicates $p < 0.01$.

Table 6: Assortativity and father-son earnings persistence

	(1)	(2)	(3)	(4)
First step regression				
Dependent variable: parents' assortativity				
Constant		yes	yes	yes
Birth decade $\times$ birth region $\times$ race indicators for each parent			yes	yes
Education decile indicators for each parent				yes
R^2		0.00	0.36	0.43
Second step regression				
Dependent variable: child's earnings				
Assortativity residual $\times$ father's earnings		0.36	0.88**	1.13***
		(0.42)	(0.41)	(0.40)
Assortativity residual		0.02	-0.04	-0.30
		(0.26)	(0.28)	(0.28)
Father's earnings	0.40***	0.39***	0.39***	0.39***
	(0.05)	(0.05)	(0.05)	(0.05)
Estimated effect of assortativity		0.04	0.10	0.12

Notes: $N = 1052$. All second-step regressions also include a constant and control for a quartic in father's age relative to 40, a quartic in child's age relative to 40, and father's earnings interacted with a quartic in child's age relative to 40, in order to address lifecycle biases (see section 5 for details). Estimated effect of assortativity refers to the difference between predicted persistence at the observed mean value of assortativity and predicted persistence at the value of assortativity that would prevail if parents were randomly matched; see text for details. Standard errors, in parentheses, are robust to heteroskedasticity and to clustering on PSID family ID. For tests of the null hypothesis that the regression parameter is zero, * indicates $p < 0.10$, ** indicates $p < 0.05$, and *** indicates $p < 0.01$.

Table 7: Assortativity and father-daughter earnings persistence

	(1)	(2)	(3)	(4)
First step regression				
Dependent variable: parents' assortativity				
Constant		yes	yes	yes
Birth decade $\times$ birth region $\times$ race indicators for each parent			yes	yes
Education decile indicators for each parent				yes
R^2		0.00	0.37	0.43
Second step regression				
Dependent variable: child's earnings				
Assortativity residual $\times$ father's earnings		0.32	0.50	0.84
		(0.62)	(0.84)	(0.85)
Assortativity residual		-0.16	0.07	-0.08
		(0.35)	(0.50)	(0.53)
Father's earnings	0.27^{***}	0.27^{***}	0.28^{***}	0.28^{***}
	(0.07)	(0.07)	(0.07)	(0.07)
Estimated effect of assortativity		0.04	0.06	0.10

Notes: $N = 1019$. All second-step regressions also include a constant and control for a quartic in father's age relative to 40, a quartic in child's age relative to 40, and father's earnings interacted with a quartic in child's age relative to 40, in order to address lifecycle biases (see section 5 for details). Estimated effect of assortativity refers to the difference between predicted persistence at the observed mean value of assortativity and predicted persistence at the value of assortativity that would prevail if parents were randomly matched; see text for details. Standard errors, in parentheses, are robust to heteroskedasticity and to clustering on PSID family ID. For tests of the null hypothesis that the regression parameter is zero, * indicates $p < 0.10$, ** indicates $p < 0.05$, and *** indicates $p < 0.01$.