The intergenerational transmission of education: New evidence from adoptions in the United States*

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Abstract

This article examines the influence of parental education on children's grade-for-age using a large sample of adoptees drawn from the American Community Survey between 2008 and 2014. The results show that mother's education is not an important determinant of the education of adopted children, despite statistically significant effects for own-birth children. The results for fathers are different. Among adopted white children, the effect of father's education is shown to be a statistically significant determinant of grade retention. However, among black children, adoptive father's education does not appear to have any discernible effect on children's education. A range of sensitivity tests are undertaken to check the validity of these results. The differences in these patterns between white and black students suggest the presence of racial differences in the intergenerational transmission of education.

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1. Introduction

It is widely documented that more educated parents have more educated children[1]. Two explanations for this intergenerational association are considered in the literature. The first reasons that parental education constitutes a nurturing effect in determining children's educational outcomes. In this case children raised by educated parents have an advantage in educational institutions (Becker and Tomes 1986; Haveman and Wolfe 1995). The second sees that nature rather than nurture is the dominant factor in educational persistence across generations (Hernstein and Murray 1994). In this case, the schooling of parents does not translate into children's schooling. Rather children's ability to do well in school is primarily inherited from their parents. For the development of education policy, understanding why parental education influences children's education is important. For example, if parental schooling is largely responsible for creating the conditions in which children do well in school, increasing the schooling of one generation will improve the schooling of the next generation, and inequality in educational opportunity will be reduced.

Three different approaches have most commonly been employed in the recent literature to control for the role of unobserved endowments in educational persistence across generations (see, for a review, Holmlund et al. 2011). The first approach looks at variation in the level of education among twins and that of their children (Antonovics and Goldberger 2005; Behrman and Rosenzweig 2002; Bingley et al. 2009; Haegeland et al. 2010; Holmlund et al. 2011). A second approach relies on instrumental variables, typically using either variation in compulsory schooling laws, tuition fees or college location (Black et al. 2005; Carneiro et al. 2013; Chevalier 2004; Chevalier et al. 2013; Farré 2012; de Haan 2011; Holmlund et al. 2011; Maurin and McNally 2008; Oreopoulos et al. 2006; Page 2006). The third strategy, which is the one used in this paper, compares children who are their parents' own birth children to children who are adopted (Bjorklund et al. 2006; Bingley et al. 2009; Dearden et al. 1997; Haegeland et al. 2010; Holmlund et al. 2011; Plug 2004; Sacerdote 2002, 2007). This strategy relies on the idea that if adopted children are not genetically linked to their parents, any relationship between the schooling of adoptees and their adoptive parents cannot be driven by related genetic ability.

[1] Haveman and Wolfe (1995) and Behrman (1997) provide extensive surveys of the earlier literature on the intergenerational transmission of education.

Generally economic studies than use adoptees are rare and often rely on small samples that are not population representative. Most previous intergenerational-mobility studies involve regressing the schooling outcomes of children on the same schooling outcomes of parents, mostly measured by years of schooling, test scores, or the probability of college attendance. An early contribution by Dearden et al. (1997) using a small sample of British adoptees found that father's education has an important effect on son's education which is similar to that for natural fathers and sons. Sacerdote (2002), also using a small number of adoptees from the National Longitudinal Survey of Youths (NLSY79), found that both father's and mother's education has a positive and statistically significant effect on children's education. Plug (2004), using a larger sample of adoptees from the Wisconsin Longitudinal Survey, found a positive effect of father's education on the child's education, but no significant effect for mother's education after accounting for assortative mating. Sacerdote (2007), using information on Korean-American adoptees, found that mother's education as well as father's education matters for child education. Employing a similar approach, Haegeland et al. (2010) used adopted children for Norway who were Korean-born and found that mother's education, but not father's education, affects children's school exam scores at age 16. An important development in adoption studies has been the use of data that contain information on adopted children, their adoptive parents, and their biological parents. Björklund et al. (2006), using administrative Swedish data, found that the impact of father's education works equally through genes and upbringing, but that the effects from mother's education is predominantly driven by genetics. Tsou et al. (2012) carried out a similar exercise with Taiwanese data on both adopted children's biological and adoptive parents. They found that both adoptive father's and mother's education has a causal effect on children's education.

This is the first attempt to use a large nationally representative dataset for the United States to estimate the effect of parental schooling on children's educational progression through school. The analysis is based on a large sample of adopted and own-birth children taken from the 2008-2014 American Community Survey (ACS). This source is extremely useful as the relevance of adoption results for the design of education policy largely depends on their generalization to a wider population. To date there are only four studies that examine the impact of parents' education on young children's intermediate educational outcomes, measured as test scores or grade repetition (Carneiro et al. 2013; Haegeland et al. 2010; Maurin and McNally 2008; Oreopoulos et al. 2006). The present study is closest to the work of Oreopoulos et al. (2006) who exploited compulsory schooling laws to examine the causal effect of parental schooling on child's schooling using the 1960, 1970 and 1980 US censuses. They found that increasing the education of either parent significantly reduces the probability that a child will repeat a grade. An advantage of using adoption data from the ACS is that father's and mother's schooling can be entered simultaneously in the same regression to identify the partial effects of each parent's education on their child's schooling. As a result I am able to look at gender-specific education policies and expand the research of Oreopoulos et al. (2006). This study also extends the adoption study of Plug (2004) for the US to intermediate educational outcomes. This is of particular interest to economists as parental inputs are thought to have the largest effects on schooling outcomes when children are young (Carneiro and Heckman, 2003; Cunha et al. 2010; Heckman and Masterov 2007). Also, evidence on the potential heterogeneity of parental education effects for various population subgroups is limited. By taking advantage of the large sample of adoptees in the ACS, this paper attempts to increase what is known by investigating how education transmission varies with a number of characteristics including gender, race and grade level. In doing so this is the first study to provide estimates of the effects of parents' education on children's education using a separate sample of black adoptees. This paper further distinguishes itself by using more recent data than previous work as the impact of parental education may have changed over time.

There are a number of considerations that are common to adoption analyses which complicate matters when it comes to making strong inferences from adoption estimates. Accordingly, I conduct a series of sensitivity tests to address the potential problems with the adoptee sample. These results show that while mother's education affects own-birth children's schooling, it does not significantly affect the education of adopted children[2]. This is true for both white and black children. Father's education affects the education of both biological and adopted white children. For black children, adoptive father's educational input does not appear to impact grade progression, regardless of grade level.

This paper continues as follows. Section two provides a description of the data. Section three describes the model. Section four discusses the results including an extensive series of sensitivity tests. Section five presents some concluding comments.

[2] These results are remarkably consistent with those of Plug (2004) for the US.

2. Data

The data for this paper is extracted from the Integrated Public Use Micro Sample (IPUMS) for the ACS between 2008 and 2014. An important strength of this data is that it provides a large nationally representative sample that contains information on the exact relationship to each child within the household for those parents who serve as the head of household (reference person) but also for their husbands and wives. This feature of the data is particularly relevant because it allows us to define a child as adopted if they are adopted by both (non-biological) parents. Given that a key identifying assumption is that adopted children are genetically unrelated to their family of rearing, it is important to eliminate related adoptions from the final sample. The number of related adopted, particularly through stepparents adopting stepchildren, in the US is substantial. Using the detailed coding on children's relationships to their parents in the ACS I can remove all step-parent adoptions from my sample[3]. Another source of related adoptions are those where grandparents adopt their grandchildren. Although the ACS does not clearly identify such adoptions, prospective parents are usually no more than 50 years older than the child at the time of adoption[4]. Therefore, in an attempt to also remove from my sample such adoptions, I delete all families where the mother is more than 50 years older than the child in question. In the past many adoption agencies used a rule of thumb that parents should not be more than 40 years older than the child. In robustness checks described below, I also provide estimates for the sample of families in which the age difference between the mother and child is no more than 40 years.

Another benefit of the ACS is that it contains information on each child's grade level attainment along with information on the education of the child's parents. I adopt a procedure similar to the one described by Oreopoulos et al. (2006) and use information on the child's grade level at the time of the survey, together with information on the child's age, to determine whether or not the child has been held back a grade in school. The practice of holding a student back a grade impacts significant numbers of children in the US. In most US states, progression from one school grade to the next largely depends on test-based criteria (Hauser et al. 2007). Grade retention is an indication of severe academic problems among children and is associated with serious long-term consequences: children who are over age

[3] In the ACS data 25% of adoptees are the stepchildren of their adoptive fathers or mothers.
[4] In the US, there is no legal upper age limit for individuals who want to adopt a child (Department of Health and Human Services 2016).

for grade find it more difficult to catch up academically later, are less likely to finish high school and less likely to attend college (see, for a review, Andrew 2014). This suggests that if one can obtain estimates of the effect of parental education on the probability of a child repeating a grade, one will also shed light on the effects of parental education on children's lifetime educational outcomes.

Determining whether or not a child has been held back in school is complicated by the fact that there is variation across states in the minimum age at school entry and the degree to which school districts comply with those dates. In this study a child is defined as "behind" if their highest completed grade at the time of the survey is lower than the median for their age, quarter of birth, state, and survey year cell. That is, I have estimated the grade a child normally would have completed based on the median grade reached among those who are the same age, born in the same birth quarter, live in the same state, and observed in the same census year. A child below the median is then classified as behind a grade at school. From the way it is defined this measure may also include children who are over age for grade because they entered school late and not because they were required to repeat a grade. Nevertheless, this variable importantly identifies whether children are progressing in school with their cohort[5]. For parental education, I create dummy variables to distinguish between parents who have completed grade 12 (high school) and those who have obtained some college or university education. The default is those who left school before grade 12[6].

The analysis focuses on children ages 7 to 15 years. Children younger than age 7 are excluded because they would not have had the chance to repeat a grade while children over the age of 15 are excluded as the ACS does not follow children who have left home. Since older children have had more of an opportunity to repeat a grade, and there may also be possible gender differences in grade repetition, all regressions include controls for year of birth and gender.

For both own-birth children and adopted children, I compose my sample of families from those with two biological or two adopted parents who are married at the time of the survey.

[5] Using the modal grade rather than the median grade to assign a child as behind (if they are below the modal grade for their age) produces results that are virtually identical to those reported in the present paper.
[6] Previous work by Oreopoulos et al. (2006) highlighted nonlinearities in years of schooling.

The number of original observations in the ACS equals 1,536,135 of whom 45,307 were adopted by both parents. I drop 74,240 stepchildren from the own-birth children sample. Of the 45,307 adopted children, I identified 4,662 as special needs children and 7,902 foreign-born adoptees. I delete all foreign-born adoptees and restrict the data to domestically-born children. Special needs children were identified in the data by a cognitive or ambulatory difficulty. As in previous work using adoption data, these children are removed from the main part of the analysis because prospective parents are given the option to specify that they would be open to adopting a child with special needs or a disability in the US. Thus, the exclusion of these children from my main sample allows me to obtain an estimate of the effect of parental education that is not biased by the selection of special needs adoptees into families. Special needs adoptees are analysed separately as part of the robustness checks. After excluding all other observations with missing values on variables used in this study, I retain 1,338,850 children of whom 29,303 are domestically-born adoptees.

Table 1 reports means and standard deviations of the variables used in this study for domestically-born adoptee and own-birth children. The data show that adopted children are quite similar to own-birth children when it comes to most summary characteristics with the exception of race and the outcome variable[7]. Consistent with the literature which finds that adopted children generally fare worse than biological children in terms of completed education, the summary statistics show that adopted children fare worse than biological children in terms of higher grade retention. The fraction of adopted children held back at school is 26 percent compared to 22 percent of children who live with their natural parents. Also, the descriptive statistics reveal that adopted children are about twice as likely to be black than own-birth children. It is noteworthy that adoptive families are fairly evenly distributed across the parental education distribution.

[7] Previous adoption studies for the US and other countries have generally found that adoptive parents have levels of education and incomes that far exceed those of other parents (Bjorklund et al. 2006; Haegeland et al. 2010; Holmlund et al. 2011; Plug 2004; Sacerdote 2002, 2007). The close resemblance between adopted and own-birth parents in the statistics reported in the present study is attributable to the fact that my sample of own-birth children is restricted to children who are raised by both their biological parents who are married at the time of the survey. Furthermore, the adoption sample is restricted to children born in the US. In analysis not reported I also looked at the educational credentials and income levels of adoptive parents of foreign-born children in the recent ACS data. Similar to other studies, I find that the adoptive parents of foreign-born children have education credentials and income levels significantly above those of other parents.

3. Empirical model

The following model depicts the typical equation used by researchers studying intergenerational educational mobility where both parents have an effect on their children's education:

$$S_i = \beta_0 + \beta_1 S_i^F + \beta_2 A_i^F + f_i^F + \beta_3 S_i^M + \beta_4 A_i^M + f_i^M + \varepsilon_i \qquad (1)$$

Here S_i is a measure of schooling for child i, S_i^F denotes the schooling of the father, S_i^M gives the schooling of the mother, A_i^F and A_i^M are the unobserved heritable endowment of both parents, and f_i^F and f_i^M are also unobserved endowments that are independent of genes and express the child-rearing talents of both parents. The error term is denoted by ε_i which represents the effects of other factors that are uncorrelated with parental education. β_1 and β_3 indicate the strength of the intergenerational schooling correlation for fathers and mothers, respectively. This effect should ideally capture the impact that parental schooling has on the quantity and quality of inputs, including parental time provided to their children, net of the effects that are genetically driven. However, with samples of parents and their own-birth children, estimates of these parameters are likely to be biased upwards (in absolute terms) due to the fact that heritable endowments cannot be observed. This paper uses the adoption strategy to eliminate this source of bias and accurately estimate the intergenerational parameters.

The validity of the adoption strategy rests on the assumption that the unobserved heritable endowments of the adoptees birth and rearing parents are uncorrelated, which is to say that β_2 and β_4 are zero. If this assumption holds, the adoptees equation is reduced to:

$$S_i = \beta_0 + \beta_1 S_i^F + f_i^F + \beta_3 S_i^M + f_i^M + \varepsilon_i \qquad (2)$$

Estimates of the intergenerational correlation of education on samples of adoptees based on this model should yield accurate estimates for the entire population under five additional assumptions. First, adoptees are randomly assigned to their families of rearing at the start of their lives. If adoption agencies use information about the biological parents to match children to adoptive parents, then pre- and post-environmental characteristics will be correlated, yielding biased coefficients. If children are moved with a substantial delay to their adopting families, the influence of their adoptive parents will be diminished. Second, adopted children are drawn from the same distribution of children as biological children. That is, adopted children have the same pre-birth characteristics as biological children. Third, natural and adoptive parents are drawn from the same distribution of parents. That is, adoptive parents provide the same post-birth environment as natural parents. Fourth, parents treat their adopted and non-adopted children similarly. Finally, it must also be assumed that non-genetic child-rearing skills and parental education are unrelated. If this assumption does not hold, child-rearing endowments when omitted would yield biased estimates of β_1 and β_3. In the results section I will discuss the potential sensitivity of my estimates to the violation of these assumptions.

4. Results

Table 2 displays the marginal-effect estimates of parental education from a probit model for the likelihood of a child repeating a grade. All regressions include an intercept and controls for the child's year of birth, gender, race, state, and survey year. Standard errors are robust to heteroscadestivity and clustered at the family level. Each column in the table represents an alternative specification. In disaggregated analysis relegated to table 1A of the appendix, it is observed that all parameter estimates are similar for both boys and girls. Thus attention is concentrated on the effects of parental schooling for the aggregated samples of children since the separate results for boys and girls yield similar conclusions.

To begin, I focus on the schooling estimates for children who are their parents' own biological offspring. Columns (1) and (2) present the effects of father's and mother's education separately. These estimates take into account all the ways in which one parent's education affects the child's schooling including the effects of assortative mating. As expected, I find that children of more educated parents are less likely to be held back in school. The influence of the father's education is just slightly less important that of his wife's education. The magnitude of these estimates indicate that, on average, the probability that a child will repeat a grade drops by 2.4 to 3.2 percentage points if his mother has obtained a high school or college education (compared to dropping out of school). The equivalent figures for father's education range from 2.2 to 2.7 percentage points. Next, I separate out the direct effect of each parent's education from the indirect effect that comes through assortative mating by including mother's and father's education simultaneously in the same specification[8]. The results in column (3) show that the partial effect of both parents' education is reduced, but remains statistically significant. Although not directly comparable

[8] In my sample, the correlation between parents' education equals 0.55 which suggests positive assortative mating.

because of differences in the way education is defined, these estimates are consistent with the results of Oreopoulos et al. (2006) which document a statistically significant association between parents' education and that of their children.

Like the vast majority of previous intergenerational estimates, these estimates do not take into account the correlation of educational attainment with genetic ability. Some researchers argue that these estimates are biased upwards (in absolute terms) because of the transfer of unobserved ability. In the second half of the table, the influence of the genetic transmission is removed by estimating the same specifications on a sample of adoptees whose genetic endowment is uncorrelated with parental education. For adopted children, I find that the estimated effects of mother's education turn out to be close to zero and statistically insignificant. These results suggest that maternal education only matters either through the transmission of genetic abilities to offspring or through prenatal nurturing as part of the utero environment. As adopted children are genetically unrelated to their rearing parents, mother's education appears to have no post-birth nurturing effects. For fathers, education is transmitted equally to both adopted and non-adopted children. The education estimates for fathers may combine several forms of nurture that are directly or indirectly a result of education. Although these estimates are subject to several important caveats that are common to adoption studies of this kind, these results are in keeping with those of Plug (2004) who found that father's education matters for adopted children, while mother's schooling produces no effect. Similar patterns have also been found by Bjorklund et al. (2006) using Swedish adoption data and by Haegeland et al. (2010) using data for Norway.

Having found no effect of mother's education on children's education, I next conduct a number of robustness checks to see whether the baseline results presented in table 2 are driven by other factors not included in the model. One explanation for the absence of a statistically significant result for mother's education is that better educated mothers spend less time with their children, which reduces the effect of mother's education to zero in the adoption sample (Behrman and Rosenzweig 2002). This seems reasonable if the mother's attention is particularly important for adopted children. Conversely, more educated mothers typically have higher incomes and fewer children, which may give rise to better educational outcomes for their children[9]. Furthermore, I also explore the sensitivity of the main results to the introduction of a private school dummy variable as parental education is correlated with private school attendance and private schools can typically establish their own cutoff dates[10]. The regression estimates presented in table 3 aim to highlight the effects of parental education in the presence of other control variables closely related to children's educational attainment. The regression model in column (1) includes family income while the regression in column (2) also contains family size, the specification presented in column (3) adds mother's usual weekly working hours, and the regression in column (4) incorporates a dummy variable for private school attendance. The results presented in columns (1) through (4) show that the impact of education is nearly the same when family income is entered, drops only marginally when family size is added, and remains mostly unchanged when mother's working hours and private school attendance are included. Thus, the main effect of paternal education on children's schooling is not being transmitted via these control variables, and neither can these controls account for the absence of a statistically significant effect for mother's education. For biological children, the coefficient on family income is small but statistically significant indicating that an increase in family income is associated with a decrease in the probability of a child repeating a grade. For adopted children, family income has no statistically significant impact on children's schooling[11]. One explanation for the difference between these samples is that biological children share the benefits of their parental genes which run through family income. Consistent with the quantity-quality hypothesis, the coefficient on the number of siblings is positive and statistically significant in both the biological and adoptee samples. Each additional child in the family increases the probability of grade retention by approximately 1.1 percentage point in the biological sample and 2.1 percentage points in the adoptee sample. As the educational coefficients are largely insensitive to the addition of family size, these results suggest that the variation in the number of children between adoptive and non-adoptive families is not responsible for the difference

[9] There is a large body of research on the benefits of higher income for the education of children (Becker and Tomes 1985; Haveman and Wolfe 1995, Duncan and Brooks-Gunn 1997). The number of siblings can also affect the education of children because with fewer children parents have more time and money to devote to each child (Becker and Lewis 1973).
[10] Previous research by Datar (2006) reveals that the cutoff dates in private and charter schools do not differ markedly from the state specified cutoff date. All public schools in the US are required to follow state school-starting age requirements.
[11] These results are also in line with the US literature in this area which suggests that even large changes in income result in only small increases in children's test scores (Blau 1997; Mayer 1997)

in the intergenerational schooling estimates between adopted and non-adopted children. In both the biological and the adopted samples of children, the effect of parents' education on children's educational progress is virtually unaffected by including how much the mother usually works. Although I observe that the coefficients on working hours are negative and statistically significant, resolving the endogeneity of these variables is not my current focus[12]. Finally, the estimates suggest that attending a private school increases the probability of being held back a grade by 1.8 percentage points in the biological sample and 2.0 percentage points in the adopted sample. In both the adopted and biological samples, the coefficients on father's and mother's education remain virtually the same whether or not the private school dummy is included as an additional regressor.

Additional robustness checks

My estimates thus far indicate that maternal schooling does not matter for the schooling outcomes of adoptees. The question naturally arises whether I can generalise my findings from adoptees to the full population of own-birth children and parents. In order to address this question, I undertake a series of sensitivity checks. To begin with there are a number of reasons why adopted children may not respond to parental education in the same way as own-birth children. One is that mothers may invest less in their adopted children than in their own-birth children[13]. To explore how serious differences in treatment may be I perform two tests. In the first test, I estimate the effect of parental education on the likelihood of a child attending a private school. This analysis is insightful because it focuses on the allocation of investments made in children rather than children's outcomes. About one in seven children in my sample are enrolled in a private school. The results presented in columns (1) and (2) of table 4 report estimates that use own and adoptee samples, respectively. I find that the effects of mother's and father's education for the adopted sample resemble those for the biological sample. These results indicate that adopted children are treated the same as biological children.

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[12] These results should be interpreted with caution and do not necessarily imply that spending more time in the labour market improves a child's grade progression but instead may reflect some unobserved variable that drives both labour market activity and grade promotion (Waldfogel 2006).

[13] Case et al. (2000, 2001) put forward the Cinderella motive where mothers invest more in their natural children (to protect their own genetic material) than in their adopted children.

Although the vast majority of adoptive parents have no birth children of their own, in the second test it would be interesting to see if this result holds up for families where there are both natural and adopted children. The estimated effects reported in column (3) are for adoptees brought up without own-birth siblings and in column (4) for adoptees brought up with own-birth children. There are virtually no differences between maternal schooling effects among adoptees with and without own-birth siblings. To further corroborate my main results, I replace the dependent variable with grade retention in the next two columns of table 4 and show that mother's education has no effect on the likelihood of being left behind at school for both adopted children with and without own-birth siblings. This evidence provides further support that my results for mothers are not tainted by treatment differentials.

Another argument put forward to explain my results is that they are downward biased if adoptive mothers are different from other mothers in ways related to maternal schooling effects. For example, mothers with low levels of education who adopt children are likely to have higher than average unobservable parenting characteristics. A way to investigate this issue proposed by Plug (2004) is to estimate the model using own-birth children who are brought up with adopted siblings. In column (7) of table 4, the sample is restricted to own-birth children who are raised by adoptive parents**.** If the education estimates are very different from those of own-birth children without adopted siblings, which are reported in column (8), one needs to worry about unobserved characteristics in adopting families. The magnitudes of the coefficients on mother's education variables illustrate the same pattern in both columns, though the standard errors are larger in column (7). These results indicate that unobserved parenting skills are not correlated with the impact schooling has on the probability of a child falling behind in school.

Another possible explanation for the difference in the estimates of education for fathers and mothers is that these results might reflect selection effects that are possibly different for men and women. This could occur if better educated women are more likely to adopt a child with a troubled history. One may suspect that estimates of the effect of maternal education that do not correct for this sort of negative selection will be biased towards zero. While this cannot be directly observed in the data, a check on this possibility is to examine how the willingness of couples to adopt a special needs child varies with the wife's and husband's education [14]. Special needs children are not placed in their adoptive families at random, as already discussed. The first column of table 5 presents the results from a probit model on an extended sample of adopted children that includes special needs children, with the dependent variable equal to 1 if the adoptee is a special needs child[15]. The results imply that mother's education is positively associated with the likelihood of adopting a special needs child, whereas the coefficient on father's education is close to zero and statistically insignificant. One way to assess how this selection issue affects the transmission coefficients for men and women is to compare the estimates of parental education obtained from a sample of adopted children with special needs to those for other adoptees without special needs[16]. The results of this analysis are displayed in the second and third columns of table 5. As previously reported, for the sample of adopted children without special needs the transmission coefficients on mother's education are small and never statistically significant. For the sample of adoptees that is restricted to special needs children, the coefficients (standard errors) on mother's education are relatively large and statistically significant varying between -0.095 (0.036) and -0.085 (0.038)[17]. Another result displayed in this table reveals that the magnitude of the coefficients on mother's education is much smaller in the sample of own-birth children with special needs than in the sample of adopted children with special needs. This is unexpected since heritable endowments are thought to be correlated with education. The most natural explanation for this result is that better educated women who have on average better parenting skills than other women choose to adopt special needs children. The equivalent results for father's education are both small and generally statistically insignificant in both the sample of adopted and own-birth children with special needs. Taken together, these results imply that selectivity from this sort of source in the adoption data is unlikely to affect the estimates of

[14] Also as an additional check, in analysis not reported, for a sample of domestically-born children with two white adoptive parents, I constructed a binary dependent variable that takes a value equal to 1 if they adopted a black child and a value of zero if they adopted a white child. From this regression the coefficients on mother's and father's education, which are statistically insignificant, do not provide evidence of selection.

[15] All regressions include controls for the child's gender, year of birth, race, state, survey year, family income, family size, mother's working hours and private school.

[16] The fraction of special needs children behind at school is 37% compared with 27% for other adopted children.

[17] These coefficients are remarkably close to those estimated by Sacerdote (2007) for a sample of foreign-born adoptees from South Korea to the US. Sacerdote (2007) reported an estimate (standard error) on the binary variable "Has 4+ Years of College" of 0.102 (0.034) which indicates that a child will on average obtain 0.102 years of additional education if their mother has four or more years of college education.

father's education and unlikely to bias downwards (in absolute terms) the effects of mother's education.

There are other sources of bias that I cannot address using the data at hand which may explain my result for mother's education. One is that adoptees may differ in systematic ways from non-adopted children. Sample characteristics presented in table 1 indicate that adoptees are more likely to be held back at school, even though they grow up in families similar to those of other children. One could argue that the slower progression of adopted children through school could be attributable to their lower genetic endowments as adopted children are likely to be born from disadvantaged families. The ACS does not contain any measure of children's genetic ability that can be used to test directly whether these characteristics are confounding the schooling estimates. However, Neiss and Rowe (2000) using the National Longitudinal Study of Adolescent Health Survey, find that the IQ scores of adopted children are practically identical to those for own-birth children. Their evidence suggests that the higher rate of grade repetition among adoptees is unlikely to be due to deficits in their genetic ability.

A second source of potential bias arises from the selection of adoptees if some parents adopt children from their relatives. Consequently, some adopted children might still have genetic links with their adoptive families. The share of adoptees brought up by genetically-related families would push the estimated impact of parental education upwards (in absolute terms). Because the maternal schooling estimates turn out to be small and statistically insignificant, related adoptees do not appear to be driving these results. There may be some merit to this argument with respect to paternal schooling estimates, but the ACS data does not distinguish between these types of bloodlines for adopted children. Arguably it would seem reasonable to assume that the paternal estimates for adoptive children are genetically unbiased since my sample excluded almost all related adoptions by eliminating from the sample stepparents who adopted children whom their partners brought into the marriage (Stolley 1993). Having stripped out these observations from my sample, I should have almost entirely removed any genetic effect in the intergenerational estimates for adopted children, suggesting the source of the relationship for fathers is not driven by genetics.

A third concern arises with respect to the age adoptees are placed in their adoptive families. I have been working under the assumption that adopted children are placed in their adoptive families at birth and receive the full impact of their adoptive parents' education. The omission of placement age as a control variable may undermine the intergenerational transmission of mother's schooling if a substantial number of children were not adopted close to birth. This is unlikely to seriously bias my estimated effects since prior evidence shows that the vast majority of adoptees in the US are placed with their adoptive families within the first year of birth (Stolley 1993)[18].

Heterogeneous effects

By looking at the aggregate sample, important differences across various subgroups of the population might be missed. The large sample size of the ACS data allows for the exploration of various sources of potential heterogeneity that are not always feasible in adoption research. The descriptive statistics presented in appendix table 2A show that children in earlier grades are more likely to be held back at school than children in later grades. Thus one might expect the effects of parental education to be stronger among older children. The summary statistics also show that white children, compared to black children, are more likely to attend a private school and come from more advantageous family backgrounds as measured by family income. However, no substantial differences in grade repetition are obvious between white and black children. Thus I do not have strong priors in terms of whether transmission coefficients should be stronger for white or black children.

The regression results for the sample divided according to the race of the child and further subdivided into children before and after grade six are presented in table 6. The top rows include the results for own-birth children while the bottom rows contain the results for adopted children. All regressions include controls for the child's gender, year of birth, state, survey year, family size, family income, mother's working hours, and private school attendance. Disaggregating the results by race reveals substantial heterogeneity. The results for own-birth children of white ethnic origin are presented in the first three columns of the upper panel of the table. For these children, the effects of mother's and father's education are always negative and statistically significant regardless of whether the child is below or above the sixth grade at the time of the survey. For the entire sample of white adoptees, the effects

[18] Stolley (1993) reports that 81% of children placed for adoption in the US are placed before age 1 and 86% are placed before age 2. Our sample eliminates most children who are likely to be placed at older ages. These include adopted stepchildren, international adoptees and special needs adoptions.

of father's education are statistically significant while the results for mother's education are not statistically different from zero. The disaggregated results show that father's education appears to matter for students in both higher and lower grade groups. For the subsample of students in early grade levels, the coefficients on father's education imply a reduction in the probability of retention of between 3.5 and 5.0 percentage points. For students in later grade levels, the effects of father's education are between 4.7 and 5.3 percentage points. This pattern of results is consistent with the idea that the children of parents with higher levels of education are more able to keep up in school than otherwise similar children from less educated backgrounds.

The next set of results presented in the remaining columns of table 6 show the equivalent estimates for black children. In contrast to the strong correlation between parents' and their biological children's education, the education relationship between parents and their adopted children is sometimes incorrectly signed and never statistically significant. Neither the mother's nor the father's education has any discernible impact on the child's educational progress. This is true regardless of whether the child is in a grade level earlier or later than grade six.

To check the robustness of my estimates for father's education with respect to important aspects in which white and black families differ, I also analyze the potential role played by family wealth and father's labour force characteristics to distinguish their effects from father's education in determining the probability of retention. One possibility is that a substantial part of the impact of father's education arises due to the indirect effect of family wealth on children's education. I test the sensitivity of my results to this by using data on home ownership and housing valuations contained within the ACS as an indicator of family wealth[19]. The large disparity in housing wealth between black and white families that has been found in previous work is also apparent in the ACS data (Charles and Hurst 2002). Summary statistics presented in appendix table 2A highlight a much higher rate of home ownership among whites compared with blacks (85% versus 68%). Conditional upon home

[19] In the ACS the relevant variable is VALUEH, which is the owner's estimate of what the house and lot would sell for if it were on the market at the time of the survey. This data is recorded for both individuals who own their own home outright and those with a mortgage loan. For cases with zero reported housing valuations (that is non-home owners), I impute housing wealth as being equal to one. Only 17% of respondents in my data did not own their own home.

ownership, I find a white mean home valuation of $202,973 (1999 dollars) in contrast to a black mean valuation of $113,456 (1999 dollars). I further observe that the average difference in housing wealth between black and white families is larger than the average difference in income (both absolutely and relatively)[20]. Thus it is reasonable to inquire whether the results are sensitive to controlling for housing wealth as wealthier individuals can invest more heavily in their children as they transition through school.

To gain further information about the source of the beneficial effect of father's education in adopted white families, I also examine the father's contribution to family income as this may affect the magnitude of the coefficient on father's education. Descriptive statistics shown in appendix table 2A reveal that the mean share of father's income as part of total family income is 0.74 in white families and 0.60 in black families. Thus, one might be concerned that part of the effect of father's education is working through the husband's share of family income. If this were the case, the coefficient on father's education would decline in the white sample when account is separately taken of father's income in a regression that simultaneously controls for family income.

Table 7 provides results with controls for housing wealth and father's share of family income[21]. As with family income, I enter the log of housing wealth and the log of father's income in addition to the other variables controlled for in table 6. All the samples of biological children support the hypothesis that housing wealth is a statistically significant and important determinant of child retention[22]. However, no discernible effects of housing wealth are apparent in any of the adopted samples. Moreover, the effects of father's education are insensitive to these additional controls in all samples. In the white adopted sample father's education continues to be an important determinant of children's education. Thus, the pathway through which father's education affects child grade progression in white families does not appear to be primarily family wealth or the husband's share of family income.

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[20] It is commonly found in the literature that wealth gaps between whites and blacks have been much greater than income gaps (Menchik and Jianakoplos 1997).

[21] Father's income is defined as family income minus wife's total income from all sources.

[22] Boehm and Schlottmann (1999), Kane (1994) and Green and White (1997) also find that children raised in owned housing have better educational attainment than those raised in rented accommodation.

In this paper, I have looked at the effects of father's and mother's education for the sample of families where the adoptive mother is no more than 50-years older than the adopted child. One concern is that this sample of adoptive children may still include children who have been adopted by their grandparents, and thus share a genetic link. Unfortunately, I am unable to specifically identify grandchild adoptions in the ACS data. However, one way to try to purge the sample of such adoptees is to remove families where the mother is more than 40 years older than the child in question. As a sensitivity check, I re-estimate the specification presented in table 7 for white adopted children on a subsample where the age difference between the mother and the child is no more than 40. These results, which are also stratified by broad grade level, are reported in table 8. In the 40-year age difference sample the effects of father's education on child grade retention look quite similar to those estimated on the larger sample. When looking at the subgroups broken down into broad grade level, the results for the 40-year age difference subsamples though somewhat less precise are similar in magnitude to the results obtained in the 50-year age difference subsamples. Thus, it is unlikely that by using children in the larger sample the effects of father's education are biased by potentially including some adoptive grandchildren.

Given the measure of grade retention I use, another concern recognizes that a child could be in a lower grade because s/he started school late (redshirting) and not because s/he was held back by the school. Since the former (redshirting) is more likely for children born later in the year, I attempt to address this issue by breaking down the sample of white adopted children into those born before and after the 30th of June[23]. The results of this analysis are displayed in table 9 for different grade levels[24]. This table is organized such that estimates for those born in the first two quarters of the year are presented in columns one and two while estimates for those born in the last two quarters of the year are displayed in columns three and four. For those born in the first half of the year, this analysis yields somewhat larger estimates of the effects of father's education when compared with the equivalent estimates in table 7. This is true whether one looks at children before or after grade six. For those born later in the year, father's education does not appear to have a statistically significant impact on grade retention, though the coefficients are correctly signed. Thus, these results suggest that the estimates in

[23] Ideally, one would like to split the sample by quarter of birth running separate regressions for each group. However, there is not enough variation in the data to obtain precise estimates separately for each group.

[24] This analysis uses the sample of children who are no more than 50-years younger than their adoptive mothers.

table 7, if anything, understate (in absolute terms) the effects of father's education on the probability of a child being held back by the school.

In table 7 the statistically insignificant effects on father's education for black adopted children are surprising in light of the results for white adopted children. Conceivably, this could result from the effect of a large number of interracial adoptions. In particular, I am concerned that children in cross-racial adoptions are more difficult to influence by their adoptive parents. This possible selection effect may operate to generate a downward bias in the parental education estimates. Black children adopted by non-black parents comprise approximately 44% of this sample. To see whether interracial adoptions are seriously affecting the parental schooling estimates for black adoptees, I also provide results for a sample of same-race adoptions. That is, I restrict the sample to black children who were adopted by two black parents. The results from this exercise are reported in column (1) of table 10. The estimated effects of parents' education are statistically insignificant. To further explore the sensitivity of these results, I also re-ran the same specification again using a sample of black children adopted by two white parents[25]. The use of a sample of children whose adoptive parents are of a different ethnic origin virtually ensures that there is no genetic link between parents and their adoptive children. The estimated coefficients on parental schooling from this regression, which are presented in column (2) of table 10, yield the same pattern of results as obtained using the entire sample of adopted black children. Because the parental schooling estimates turn out to be the statistically insignificant in both samples, black adoptees who were adopted by white families appear not to be driving the main results. I conclude that the transmission coefficients for black adoptees are not particularly sensitive to the subsample from which they are obtained. Taken together, the results suggest that the channel through which parental education affects children's education does not appear to be the same for white and black children.

5. Conclusion

This article contributes to the general intergenerational mobility literature by estimating the educational transmission coefficients from parents to school-age children for adoptees and non-adoptees using nationally representative data from the ACS. For biological children, I find that mother's education is an important determinant of a child's schooling, measured by

[25] In relation to black couples adopting white children, there are only 24 such adoptions in my data (out of only a total of 85 white children who are not in same-race adoptive families).

grade-for-age. For adoptees, I find no effect for mother's education, once assortative mating is taken into account. These results are robust to different regression specifications that control for other variables that affect children's education. Further sensitivity tests do not show any evidence that the results are driven by the selection of more unfortunate children for adoption by better educated women. These results are similar for white and black children as well as for children before and after the sixth grade. My findings reinforce those of Plug (2004) for the United States and are similar to those reported by Bjorklund et al. (2006) for Sweden and Haegeland et al. (2010) for Norway. By contrast, in the entire sample of children, I find statistically significant effects for father's education which are similar for adopted and own-birth children. These findings suggest that father's education can be passed on from one generation to the next with heritable ability playing no important role in the intergenerational transmission of education. When the sample is divided by race, only white adopted children are responsive to improvements in father's education. Black adopted children, regardless of grade level, do not appear to benefit from increases in father's education, despite statistically significant correlations for own-birth children. As the results are robust to controls for differences in family wealth (as measured by housing valuations) and the father's share of family income, these findings are inconsistent with the view that racial differences in parental financial resources are responsible for the different effects of father's education on black and white children. Other differences in characteristics between black and white families that could potentially explain these results cannot be investigated with the data used in this article. Racial differences in norms concerning investments in children could be a possible source of racial differences in children's educational outcomes even among sets of parents with similar levels of education and wealth. Alternatively, black-white differences in norms concerning marriage may create differences in the mapping of parents' and children's human capital across generations. The task of understanding the importance of these differences in the intergenerational transmission of education remains for future research.

The results of this study were not based on the experimental ideal of random assignment of adopted children to families. The implication is that the estimates derived from the ACS data using adoptees may not be directly comparable to those that use own birth samples. Thus, I caution against a causal interpretation of the coefficients on parents' education. In sensitivity analyses, I examined how adoption might be associated with differences between adoptive and natural parents, between adopted and own-birth children, and between the ways these children are treated. These tests do not show any evidence that these factors are relevant for my main educational estimates. While my results reject the existence of post-birth educational spillovers in the case of women, it is possible that increases in women's education may have prenatal and perinatal benefits for children that are not reflected in these adoption estimates.

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Table 1. Descriptive statistics.

	Own Birth Children	Adopted Children
Repeat a grade (Behind)	0.222	0.261
	(0.415)	(0.439)
Private school	0.147	0.157
	(0.354)	(0.364)
Gender (daughter)	1.486	1.517
	(0.500)	(0.500)
Year of birth	2000	2000
	(3.269)	(3.246)
Mother's Education - No qualifications	0.070	0.055
	(0.255)	(0.227)
Mother's Education - High School	0.261	0.305
	(0.439)	(0.461)
Mother's Education - College	0.669	0.640
	(0.471)	(0.480)
Father's Education - No qualifications	0.083	0.064
	(0.275)	(0.245)
Father's Education - High School	0.298	0.325
	(0.458)	(0.468)
Father's Education - College	0.619	0.612
	(0.486)	(0.487)
Number of siblings	1.630	1.661
	(1.194)	(1.523)
White	0.802	0.737
	(0.398)	(0.440)
Black	0.053	0.113
	(0.225)	(0.316)
Other race	0.144	0.150
	(0.352)	(0.358)
Log annual family income (1999 dollars)	11.030	11.001
	(0.743)	(0.706)
Observations	1,338,850	29,303

Table 2. The effect of parental education on children's grade retention.

	(1)	(2)	(3)
Biological Children			
Mother - High School	-0.024***		-0.018***
	[0.001]		[0.002]
Mother > High School	-0.032***		-0.023***
	[0.001]		[0.002]
Father - High School		-0.022***	-0.013***
		[0.001]	[0.002]
Father > High School		-0.027***	-0.015***
		[0.001]	[0.002]
Observations	1,338,850	1,338,850	1,338,850
Adopted Children			
Mother - High School	-0.020*		-0.005
	[0.012]		[0.013]
Mother > High School	-0.017		-0.002
	[0.011]		[0.013]
Father - High School		-0.042***	-0.041***
		[0.011]	[0.011]
Father > High School		-0.036***	-0.036***
		[0.011]	[0.012]
Observations	29,303	29,303	29,303

Notes: The marginal effects are reported from Probit models. All regressions include control variables for the child's gender, year of birth, race, state and survey year. Huber-White's robust standard errors clustered at the family level are reported in brackets. * denotes statistical significant at 10%; ** denotes statistical significant at 5%; *** denotes statistical significant at 1%.

Table 3. Sensitivity of the estimates of the effect of parental education on children's grade retention to additional controls.

	(1)	(2)	(3)	(4)
Biological Children				
Mother's Education - High School	-0.017***	-0.012***	-0.010***	-0.011***
	[0.002]	[0.002]	[0.002]	[0.002]
Mother's Education - College	-0.021***	-0.015***	-0.012***	-0.013***
	[0.002]	[0.002]	[0.002]	[0.002]
Father's Education - High School	-0.012***	-0.009***	-0.009***	-0.009***
	[0.002]	[0.002]	[0.002]	[0.002]
Father's Education - College	-0.012***	-0.010***	-0.011***	-0.012***
	[0.002]	[0.002]	[0.002]	[0.002]
Log of family income	-0.004***	-0.003***	-0.002***	-0.003***
	[0.001]	[0.001]	[0.001]	[0.001]
Number of siblings		0.011***	0.010***	0.009***
		[0.000]	[0.000]	[0.000]
Mother working < 40 hrs/week			-0.006***	-0.005***
			[0.001]	[0.001]
Mother working >= 40 hrs/week			-0.014***	-0.013***
			[0.001]	[0.001]
Private school (0, 1)				0.018***
				[0.001]
Observations	1,338,850	1,338,850	1,338,850	1,338,850
Adopted Children				
Mother's Education - High School	-0.005	-0.001	0.002	0.002
	[0.013]	[0.013]	[0.013]	[0.013]
Mother's Education - College	-0.001	0.004	0.009	0.008
	[0.013]	[0.013]	[0.013]	[0.013]
Father's Education - High School	-0.041***	-0.036***	-0.036***	-0.036***
	[0.011]	[0.011]	[0.011]	[0.011]
Father's Education - College	-0.035***	-0.029**	-0.032***	-0.033***
	[0.012]	[0.012]	[0.012]	[0.012]
Log of family income	-0.001	0.001	0.004	0.003
	[0.004]	[0.004]	[0.004]	[0.004]
Number of siblings		0.021***	0.020***	0.020***
		[0.002]	[0.002]	[0.002]
Mother working < 40 hrs/week			-0.012*	-0.011*
			[0.007]	[0.007]
Mother working >= 40 hrs/week			-0.025***	-0.023***
			[0.006]	[0.006]
Private school (0, 1)				0.020***
				[0.007]
Observations	29,303	29,303	29,303	29,303

Notes: The marginal effects are reported from Probit models. All regressions include control variables for the child's gender, year of birth, race, state and survey year. Huber-White's robust standard errors clustered at the family level are reported in brackets. * denotes statistical significant at 10%; ** denotes statistical significant at 5%; *** denotes statistical significant at 1%.

Table 4. Estimates of the effect of parental education on children's grade retention and private school attendance using various subsamples.

	(1) *Own birth children*	(2) *Adopted children*	(3) *Adopted without own birth children*	(4) *Adopted with own birth children*	(5) *Adopted without own birth children*	(6) *Adopted with own birth children*	(7) *Own birth with adopted children*	(8) *Own birth without adopted children*
Dependent variable:	Private school	Private school	Private school	Private school	Behind	Behind	Behind	Behind
Mother - High School	0.027***	0.021*	0.023	0.021	-0.005	0.028	-0.003	-0.011***
	[0.002]	[0.012]	[0.014]	[0.028]	[0.014]	[0.030]	[0.021]	[0.002]
Mother - College	0.065***	0.064***	0.066***	0.061***	0.003	0.036	-0.004	-0.013***
	[0.002]	[0.011]	[0.012]	[0.023]	[0.015]	[0.029]	[0.021]	[0.002]
Father - High School	0.013***	-0.002	0.002	-0.011	-0.033**	-0.051**	-0.029	-0.009***
	[0.002]	[0.011]	[0.013]	[0.023]	[0.013]	[0.024]	[0.019]	[0.002]
Father - College	0.057***	0.049***	0.052***	0.039*	-0.027**	-0.057**	-0.040**	-0.012***
	[0.001]	[0.010]	[0.012]	[0.022]	[0.014]	[0.027]	[0.021]	[0.002]
Log family income	0.046***	0.055***	0.056***	0.053***	0.005	-0.002	0.006	-0.003***
	[0.000]	[0.003]	[0.004]	[0.007]	[0.005]	[0.009]	[0.006]	[0.001]
Private school (0, 1)					0.014*	0.038**	0.014	0.018***
					[0.008]	[0.016]	[0.011]	[0.001]
Observations	1,338,850	29,303	22,786	6,517	22,786	6,517	10,704	1,328,146

Notes: The marginal effects are reported from Probit models. All regressions include control variables for the child's gender, year of birth, race, state, survey year, mother's working hours and the number of siblings. Huber-White's robust standard errors clustered at the family level are reported in brackets. * denotes statistical significant at 10%; ** denotes statistical significant at 5%; *** denotes statistical significant at 1%.

Table 5. Estimates of the effect of parental education on the probability of adopting a special needs child and grade retention for various samples of adopted children.

	(1)	(2)	(3)	(4)
Sample:	*All adopted children*	*Adoptees without special needs*	*Adoptees with special needs*	*Own birth with special needs*
Dependent variable:	Special needs	Behind	Behind	Behind
Mother - High School	0.033***	-0.006	-0.095***	-0.033***
	[0.009]	[0.013]	[0.036]	[0.010]
Mother > High School	0.034***	0.002	-0.085**	-0.032***
	[0.008]	[0.013]	[0.038]	[0.010]
Father - High School	0.008	-0.042***	-0.023	-0.006
	[0.008]	[0.011]	[0.033]	[0.009]
Father > High School	-0.006	-0.036***	-0.035	0.008
	[0.008]	[0.012]	[0.034]	[0.009]
Log family income	-0.023***	0.008*	-0.005	0.001
	[0.003]	[0.004]	[0.013]	[0.004]
Private school (0, 1)	-0.020***	0.018**	0.061**	0.017**
	[0.005]	[0.007]	[0.024]	[0.008]
Observations	33,187	29,303	3,884	36,966

Notes: The marginal effects are reported from Probit models. All regressions include control variables for the child's gender, year of birth, race, state, survey year, mother's working hours and the number of siblings. Huber-White's robust standard errors clustered at the family level are reported in brackets. * denotes statistical significant at 10%; ** denotes statistical significant at 5%; *** denotes statistical significant at 1%.

Table 6. Estimates of the effect of parental education on grade retention: heterogeneity by race and grade level.

	White Children			Black Children		
	(1)	(2)	(3)	(4)	(5)	(6)
	Total	Grade <= 6	Grade >= 7	Total	Grade <= 6	Grade >= 7
A. Biological Children						
Mother -High School	-0.009***	-0.008***	-0.010***	-0.040***	-0.034***	-0.043***
	[0.002]	[0.003]	[0.003]	[0.007]	[0.009]	[0.009]
Mother>High School	-0.011***	-0.011***	-0.011***	-0.064***	-0.064***	-0.056***
	[0.002]	[0.003]	[0.003]	[0.008]	[0.010]	[0.011]
Father - High School	-0.010***	-0.007***	-0.013***	-0.015**	-0.019**	-0.002
	[0.002]	[0.003]	[0.003]	[0.006]	[0.009]	[0.009]
Father > High School	-0.011***	-0.005*	-0.017***	-0.029***	-0.033***	-0.016*
	[0.002]	[0.003]	[0.003]	[0.007]	[0.009]	[0.009]
Log family income	-0.001**	0.000	-0.003***	-0.022***	-0.021***	-0.022***
	[0.001]	[0.001]	[0.001]	[0.003]	[0.004]	[0.004]
Private school (0, 1)	0.017***	0.018***	0.014***	0.007	0.014*	0.003
	[0.001]	[0.002]	[0.002]	[0.005]	[0.007]	[0.007]
Observations	1,073,837	657,721	416,116	71,560	42,751	28,809
B. Adopted Children						
Mother -High School	0.014	0.008	0.012	0.001	-0.030	0.010
	[0.015]	[0.021]	[0.022]	[0.039]	[0.054]	[0.056]
Mother>High School	0.022	0.011	0.030	-0.024	-0.087	0.036
	[0.015]	[0.021]	[0.022]	[0.040]	[0.059]	[0.054]
Father - High School	-0.050***	-0.050***	-0.047**	0.024	0.033	0.020
	[0.013]	[0.018]	[0.018]	[0.038]	[0.057]	[0.049]
Father > High School	-0.046***	-0.035*	-0.053**	0.010	0.011	-0.006
	[0.014]	[0.020]	[0.021]	[0.038]	[0.057]	[0.049]
Log family income	-0.001	0.006	-0.010	-0.001	0.021	-0.018
	[0.005]	[0.007]	[0.007]	[0.013]	[0.018]	[0.018]
Private school (0, 1)	0.020**	0.028**	0.006	0.035	0.034	-0.003
	[0.008]	[0.011]	[0.012]	[0.024]	[0.033]	[0.035]
Observations	21,580	12,891	8,689	3,295	1,922	1,373

Notes: The marginal effects are reported from Probit models. All regressions include control variables for the child's gender, year of birth, race, state, survey year, mother's working hours and the number of siblings. Huber-White's robust standard errors clustered at the family level are reported in brackets. * denotes statistical significant at 10%; ** denotes statistical significant at 5%; *** denotes statistical significant at 1%.

Table 7. Sensitivity of estimates of the effect of parental education on grade retention to additional controls: heterogeneity by race and grade level results.

	White Children			Black Children		
	(1)	(2)	(3)	(4)	(5)	(6)
	Total	Grade <= 6	Grade >= 7	Total	Grade <= 6	Grade >= 7
A. Biological Children						
Mother -High School	-0.009***	-0.008***	-0.010***	-0.039***	-0.034***	-0.042***
	[0.002]	[0.003]	[0.003]	[0.007]	[0.009]	[0.009]
Mother >High School	-0.010***	-0.010***	-0.010***	-0.063***	-0.063***	-0.054***
	[0.002]	[0.003]	[0.003]	[0.008]	[0.010]	[0.011]
Father - High School	-0.009***	-0.006**	-0.012***	-0.015**	-0.019**	-0.002
	[0.002]	[0.003]	[0.003]	[0.006]	[0.009]	[0.009]
Father > High School	-0.010***	-0.004	-0.016***	-0.029***	-0.032***	-0.016*
	[0.002]	[0.003]	[0.003]	[0.007]	[0.009]	[0.009]
Log family income	0.002**	0.003***	0.000	-0.019***	-0.017***	-0.021***
	[0.001]	[0.001]	[0.001]	[0.003]	[0.004]	[0.004]
Private school (0, 1)	0.017***	0.019***	0.014***	0.009	0.015**	0.004
	[0.001]	[0.002]	[0.002]	[0.005]	[0.007]	[0.007]
Log father's income	-0.001***	-0.001**	-0.001	0.001	0.000	0.001
	[0.000]	[0.000]	[0.000]	[0.001]	[0.001]	[0.001]
Log house value	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Observations	1,073,837	657,721	416,116	71,560	42,751	28,809
B. Adopted Children						
Mother -High School	0.015	0.008	0.012	0.000	-0.030	0.004
	[0.015]	[0.021]	[0.022]	[0.039]	[0.054]	[0.056]
Mother>High School	0.023	0.012	0.030	-0.026	-0.086	0.028
	[0.015]	[0.021]	[0.022]	[0.040]	[0.059]	[0.054]
Father - High School	-0.050***	-0.049***	-0.047**	0.023	0.031	0.021
	[0.013]	[0.018]	[0.018]	[0.038]	[0.057]	[0.049]
Father > High School	-0.046***	-0.035*	-0.053**	0.008	0.009	-0.005
	[0.014]	[0.020]	[0.021]	[0.038]	[0.057]	[0.049]
Log family income	-0.004	0.004	-0.010	0.003	0.017	0.003
	[0.006]	[0.008]	[0.009]	[0.016]	[0.021]	[0.023]
Private school (0, 1)	0.020**	0.028**	0.006	0.033	0.032	-0.006
	[0.008]	[0.011]	[0.012]	[0.024]	[0.033]	[0.034]
Log father's income	0.003	0.002	0.001	-0.005	0.000	-0.018*
	[0.003]	[0.004]	[0.004]	[0.006]	[0.007]	[0.010]
Log house value	0.000	-0.001	0.000	0.002	0.002	0.002
	[0.001]	[0.001]	[0.001]	[0.002]	[0.003]	[0.003]
Observations	21,580	12,891	8,689	3,295	1,922	1,373

Notes: The marginal effects are reported from Probit models. All regressions include control variables for the child’s gender, year of birth, race, state, survey year, mother’s working hours and the number of siblings. Huber-White’s robust standard errors clustered at the family level are reported in brackets. * denotes statistical significant at 10%; ** denotes statistical significant at 5%; *** denotes statistical significant at 1%.

Table 8. Estimates of the effect of parental education on grade retention for adopted white children: Sample restricted to children where the age difference between mother and child is no more than 40 years.

	Age difference <= 50			Age difference < = 40		
	Total	Grade <= 6	Grade >= 7	Total	Grade <= 6	Grade >= 7
	(1)	(2)	(3)	(4)	(5)	(6)
Mother- High School	0.015	0.008	0.012	0.022	0.031	0.001
	[0.015]	[0.021]	[0.022]	[0.018]	[0.025]	[0.025]
Mother>High School	0.023	0.012	0.030	0.031	0.030	0.022
	[0.015]	[0.021]	[0.022]	[0.023]	[0.025]	[0.025]
Father - High School	-0.050***	-0.049***	-0.047**	-0.043***	-0.048**	-0.031
	[0.013]	[0.018]	[0.018]	[0.016]	[0.021]	[0.021]
Father > High School	-0.046***	-0.035*	-0.053**	-0.041**	-0.035	-0.039*
	[0.014]	[0.020]	[0.021]	[0.017]	[0.023]	[0.023]
Log family income	-0.004	0.004	-0.010	-0.009	-0.003	-0.014
	[0.006]	[0.008]	[0.009]	[0.007]	[0.010]	[0.010]
Private school (0, 1)	0.020**	0.028**	0.006	0.024**	0.033**	0.009
	[0.008]	[0.011]	[0.012]	[0.010]	[0.013]	[0.014]
Log father's income	0.003	0.002	0.001	0.005*	0.007	0.001
	[0.003]	[0.004]	[0.004]	[0.003]	[0.004]	[0.004]
Log house value	0.000	-0.001	0.000	0.000	0.000	-0.001
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Observations	21,580	12,891	8,689	17,102	10,030	7,072

Notes: The marginal effects are reported from Probit models. All regressions include control variables for the child's gender, year of birth, race, state, survey year, mother's working hours and the number of siblings. Huber-White's robust standard errors clustered at the family level are reported in brackets. * denotes statistical significant at 10%; ** denotes statistical significant at 5%; *** denotes statistical significant at 1%. The columns entitled "age difference <= 50" refer to a sample of adoptees where the mother is no more than 50 years older than the child, and the columns entitled "age difference <= 40" refer the a sample of adoptees where the mother is no more than 40 years older than the child.

Table 9. Estimates of the effect of parental education on grade retention for adopted white children: Sample split into children born before and after the 30th June.

Quarter of birth:	(1) Grade<=6 *1st/2nd qtr*	(2) Grade>=7 *1st/2nd qtr*	(3) Grade<=6 *3rd/4th qtr*	(4) Grade>=7 *3rd/4th qtr*
Mother - High School	0.035	0.012	-0.030	0.004
	[0.033]	[0.033]	[0.026]	[0.029]
Mother > High School	0.032	0.043	-0.024	0.007
	[0.033]	[0.032]	[0.027]	[0.029]
Father - High School	-0.071**	-0.076***	-0.033	-0.023
	[0.028]	[0.027]	[0.024]	[0.024]
Father > High School	-0.050*	-0.089***	-0.022	-0.024
	[0.030]	[0.032]	[0.025]	[0.026]
Log family income (1999 dollars)	-0.003	-0.023*	0.013	0.008
	[0.012]	[0.013]	[0.011]	[0.011]
Number of siblings	0.022***	0.008*	0.025***	0.011***
	[0.004]	[0.004]	[0.004]	[0.004]
Mother working < 40 hrs/week	-0.008	-0.032**	-0.002	-0.029**
	[0.016]	[0.016]	[0.014]	[0.014]
Mother working >= 40 hrs/week	-0.029*	-0.056***	-0.004	-0.027*
	[0.016]	[0.016]	[0.014]	[0.015]
Private school (0, 1)	0.025	0.023	0.031**	-0.009
	[0.017]	[0.018]	[0.015]	[0.016]
Log father's income (1999 dollars)	0.006	-0.004	0.000	0.003
	[0.006]	[0.006]	[0.005]	[0.005]
Log house value (1999 dollars)	0.001	0.001	-0.002	-0.002
	[0.002]	[0.002]	[0.001]	[0.002]
Observations	6,306	4,378	6,585	4,311

Notes: The marginal effects are reported from Probit models. All regressions include control variables for the child's gender, year of birth, race, state, survey year, mother's working hours and the number of siblings. Huber-White's robust standard errors clustered at the family level are reported in brackets. * denotes statistical significant at 10%; ** denotes statistical significant at 5%; *** denotes statistical significant at 1%. 1st /2nd qtr refers to the first and second quarter of the year in which the child was born i.e., before 30th June. 3rd/4th qtr refers to the third and fourth quarter of year in which the child was born i.e., after 30th June.

Table 10. Estimates of the effect of parental education on grade retention for black children adopted by black and white parents.

	(1) Adopted by two black parents	(2) Adopted by two white parents
Mother - High School	0.044	-0.026
	[0.047]	[0.126]
Mother > High School	0.005	0.019
	[0.046]	[0.126]
Father - High School	0.002	0.062
	[0.040]	[0.131]
Father > High School	-0.018	0.054
	[0.041]	[0.119]
Log family income (1999 dollars)	-0.017	0.009
	[0.022]	[0.029]
Private school (0, 1)	-0.046	0.077**
	[0.035]	[0.037]
Log father's income (1999 dollars)	-0.001	0.015
	[0.008]	[0.014]
Log house value (1999 dollars)	0.006***	-0.007
	[0.002]	[0.004]
Observations		
	1,827	1,146

Notes: The marginal effects are reported from Probit models. All regressions include control variables for the child's gender, year of birth, race, state, survey year, mother's working hours and the number of siblings. Huber-White's robust standard errors clustered at the family level are reported in brackets. * denotes statistical significant at 10%; ** denotes statistical significant at 5%; *** denotes statistical significant at 1%.

Appendix

Table 1A. The effect of parental education on children's grade retention for boys and girls separately

	Boys			Girls		
	(1)	(2)	(3)	(4)	(5)	(6)
Biological Children						
Mother - High School	-0.020***		-0.013***	-0.029***		-0.022***
	[0.002]		[0.002]	[0.002]		[0.002]
Mother > High School	-0.025***		-0.017***	-0.039***		-0.030***
	[0.002]		[0.002]	[0.002]		[0.003]
Father - High School		-0.020***	-0.014***		-0.024***	-0.012***
		[0.002]	[0.002]		[0.002]	[0.002]
Father > High School		-0.023***	-0.014***		-0.031***	-0.015***
		[0.002]	[0.002]		[0.002]	[0.002]
Observations	688,016	688,016	688,016	650,834	650,834	650,834
Adopted Children						
Mother - High School	-0.021		-0.009	-0.021		-0.005
	[0.016]		[0.018]	[0.017]		[0.018]
Mother > High School	-0.023		-0.011	-0.014		0.004
	[0.016]		[0.018]	[0.016]		[0.018]
Father - High School		-0.040***	-0.037**		-0.045***	-0.045***
		[0.015]	[0.016]		[0.015]	[0.016]
Father > High School		-0.032**	-0.028		-0.039**	-0.043**
		[0.015]	[0.017]		[0.015]	[0.017]
Observations	14,154	14,154	14,154	15,149	15,149	15,149

Notes: The marginal effects are reported from Probit models. All regressions include control variables for the child's gender, year of birth, race, state and survey year. Huber-White's robust standard errors clustered at the family level are reported in brackets. * denotes statistical significant at 10%; ** denotes statistical significant at 5%; *** denotes statistical significant at 1%.

Table 2A. Summary statistics by race and grade level

	Own-birth Children			Adopted Children		
	Total	Grade <=6	Grade>=7	Total	Grade <= 6	Grade>=7
A. White Children						
Repeat a grade (Behind)	0.223	0.256	0.171	0.264	0.301	0.210
	(0.416)	(0.437)	(0.376)	(0.441)	(0.459)	(0.407)
Private school	0.159	0.162	0.153	0.164	0.166	0.161
	(0.365)	(0.369)	(0.360)	(0.370)	(0.372)	(0.368)
Gender (daughter)	1.485	1.482	1.491	1.518	1.517	1.520
	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)
Year of birth	2000	2002	1997	2000	2001	1997
	(3.269)	(2.579)	(2.270)	(3.259)	(2.604)	(2.278)
Mother < High School	0.059	0.059	0.058	0.053	0.053	0.053
	(0.235)	(0.236)	(0.233)	(0.223)	(0.223)	(0.223)
Mother - High School	0.260	0.248	0.278	0.310	0.304	0.320
	(0.438)	(0.432)	(0.448)	(0.463)	(0.460)	(0.467)
Mother > High School	0.682	0.693	0.664	0.637	0.644	0.627
	(0.466)	(0.461)	(0.472)	(0.481)	(0.479)	(0.484)
Father < High School	0.073	0.073	0.072	0.062	0.062	0.062
	(0.260)	(0.260)	(0.259)	(0.242)	(0.242)	(0.241)
Father - High School	0.299	0.292	0.311	0.326	0.326	0.326
	(0.458)	(0.455)	(0.463)	(0.469)	(0.469)	(0.469)
Father > High School	0.628	0.635	0.617	0.612	0.612	0.612
	(0.483)	(0.481)	(0.486)	(0.487)	(0.487)	(0.487)
Number of siblings	1.634	1.694	1.539	1.590	1.670	1.470
	(1.202)	(1.198)	(1.202)	(1.472)	(1.496)	(1.429)
Family income (1999 dollars)	83,999	82,285	86,709	79,347	77,632	81,889
	(74436)	(73806)	(75341)	(69492)	(67578)	(72166)
Father income (1999 dollars)	62,003	60,880	63,777	58,321	57,254	59,903
	(65545)	(64686)	(66842)	(61116)	(59392)	(63557)
Home ownership (0, 1)	0.856	0.843	0.876	0.889	0.878	0.904
	(0.351)	(0.363)	(0.329)	(0.315)	(0.327)	(0.294)
Home value (1999 dollars)	202,973	198,046	210,760	190,412	183,245	201,042
	(283303)	(279508)	(289030)	(260432)	(246440)	(279574)
Observations	1,073,837	657,721	416,116	21,580	12,891	8,689
B. Black Children						
Repeat a grade (Behind)	0.199	0.229	0.155	0.245	0.277	0.201
	(0.399)	(0.420)	(0.362)	(0.430)	(0.448)	(0.401)
Private school	0.098	0.100	0.095	0.127	0.136	0.114
	(0.298)	(0.300)	(0.293)	(0.333)	(0.343)	(0.318)

Table 2A. Summary statistics by race and grade level (concluded)

	Own-birth Children			Adopted Children		
	Total	Grade <= 6	Grade>=7	Total	Grade <= 6	Grade>=7
Gender (daughter)	1.491	1.487	1.497	1.498	1.499	1.496
	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)
Year of birth	2000	2002	1997	2000	2001	1997
	(3.257)	(2.568)	(2.288)	(3.195)	(2.588)	(2.254)
Mother < High School	0.047	0.047	0.047	0.044	0.040	0.049
	(0.212)	(0.213)	(0.212)	(0.205)	(0.196)	(0.217)
Mother - High School	0.282	0.276	0.292	0.291	0.282	0.303
	(0.450)	(0.447)	(0.455)	(0.454)	(0.450)	(0.460)
Mother > High School	0.670	0.677	0.661	0.665	0.678	0.647
	(0.470)	(0.468)	(0.473)	(0.472)	(0.467)	(0.478)
Father < High School	0.057	0.057	0.058	0.052	0.043	0.065
	(0.233)	(0.232)	(0.234)	(0.223)	(0.203)	(0.247)
Father - High School	0.367	0.357	0.381	0.334	0.331	0.337
	(0.482)	(0.479)	(0.486)	(0.472)	(0.471)	(0.473)
Father > High School	0.576	0.586	0.561	0.614	0.626	0.597
	(0.494)	(0.493)	(0.496)	(0.487)	(0.484)	(0.491)
Number of siblings	1.690	1.762	1.582	1.943	2.024	1.831
	(1.275)	(1.277)	(1.265)	(1.753)	(1.746)	(1.758)
Family income (1999 dollars)	63,770	62,295	65,961	68,948	68,407	69,705
	(49766)	(49484)	(50101)	(54047)	(54104)	(53978)
Father income (1999 dollars)	38,649	37,771	39,953	45,765	45,232	46,511
	(38099)	(37548)	(38867)	(43304)	(42262)	(44728)
Home ownership (0, 1)	0.679	0.653	0.718	0.839	0.832	0.849
	(0.467)	(0.476)	(0.450)	(0.368)	(0.374)	(0.358)
Home value (1999 dollars)	113,456	108,151	121,330	147,919	146,575	149,801
	(171258)	(164236)	(180897)	(182385)	(180371)	(185218)
Observations	71,560	42,751	28,809	3,295	1,922	1,373