HOW LARGE ARE THE EFFECTS FROM CHANGES IN FAMILY ENVIRONMENT? A STUDY OF KOREAN AMERICAN ADOPTEES*

BRUCE SACERDOTE

I analyze a new set of data on Korean American adoptees who were quasi-randomly assigned to adoptive families. I find large effects on adoptees' education, income, and health from assignment to parents with more education and from assignment to smaller families. Parental education and family size are significantly more correlated with adoptee outcomes than are parental income or neighborhood characteristics. Outcomes such as drinking, smoking, and the selectivity of college attended are more determined by nurture than is educational attainment. Using the standard behavioral genetics variance decomposition, I find that shared family environment explains 14 percent of the variation in educational attainment, 35 percent of the variation in college selectivity, and 33 percent of the variation in drinking behavior.

I. INTRODUCTION

Social scientists, policy makers, and parents everywhere are interested in the degree to which children's behavior and outcomes are determined by nature, nurture, and the interaction between the two. This paper uses at adoption in infancy to identify the effects of large scale changes in family environment on children's outcomes. I compare outcomes for children assigned to smaller families with highly educated parents to outcomes for children assigned to large families where neither parent has a college degree. The quasi random assignment of children to families in the data allows me to give the estimates a causal interpretation. Children assigned to the high education, small families are twice as likely to graduate from a college ranked by US News & World Report, have an additional .75 years of education, and are 16 percent more likely to complete four years of college. My

* I thank Holt International Children's Services and particularly Laura Hofer and Karla Miller for their help in gathering data and information on international adoptions. The National Science Foundation provided generous funding for the entire project including the data collection. I thank Anne Ladenburger, Abigail Ridgeway, Ariel Stern-Markowitz, and Celia Carmen for tireless research assistance and valuable suggestions. Larry Katz and Edward Glaeser provided superb editing. I thank Joseph Altonij for very useful comments. Heroic efforts from two anonymous referees greatly improved the paper. Jonathan Gruber and Kwabena Gyimah-Brempong advised me on the design of the study. Seminar participants at NBER Summer Institute, Syracuse, Cornell, Case-Western, Brigham Young University, Vanderbilt, University of South Florida, University of Colorado at Denver and elsewhere contributed very helpful comments.

The Quarterly Journal of Economics, February 2007

estimated effects may provide a useful context for understanding how more typically observed changes in neighborhoods, family income, peer quality, or school quality translate into children's outcomes.

The adoptees in the study are Korean Americans placed by Holt International Children's Services during 1964–1985. The adoptees are quasi randomly assigned to families, conditional on the family being certified by Holt to adopt. Holt uses a queuing (first-come first-served) policy to assign Korean adoptees to families. As a result, assignment of children to families is effectively random conditional on the adoptee's cohort and gender. I provide empirical evidence showing that adoptees' pre-treatment characteristics are uncorrelated with adoptive family characteristics.

The data come from Holt's records and from a survey of adoptees and their families conducted during 2004–2005. Holt and I originally targeted a sample of adoptees ages 24–34 in 2004, but collected data for all adoptees and nonadoptees in the family. The sample is much larger than most existing adoption studies (with the exception of Bjorkland, Lindahl, and Plug [2006]) and we collected data for a wide range of outcomes. Two chief disadvantages of my data are that the response rate to the initial survey was low at 34 percent and that I rely on parental reports of adult adoptee outcomes. To deal with these issues Holt and I resurveyed a sample of the non-respondents and I show that responses are not significantly correlated with child outcomes. We also surveyed directly a smaller sample of the adoptees and nonadoptees and I demonstrate the high degree of correspondence between their responses and their parents.

I apply the standard behavioral genetics framework (see Plomin, DeFries, and Fulker [1988]) to decompose the variance in child outcomes into variance explained by environment (nurture), variance explained by genes or initial endowments (nature), and variance explained by non-shared environment. While educational attainment and income are frequently the focus of economic studies, these are among the outcomes least affected by differences in family environment. In contrast, the selectivity of college attended has a much larger nurture component and the explained variation in "social" outcomes like drinking behavior and marital status appears to be almost entirely nurture based.

I.A. *A Brief History of Holt, Korean American Adoption, and the Assignment Process*

Harry and Bertha Holt pioneered international adoption in Seoul, Korea in 1955. The Holts had built a fortune in lumber and farming in Oregon and were so moved by the plight of Korean War orphans that they lobbied Congress for a special act to adopt eight of them. When they returned home with their new children, they discovered that many other Americans also wished to adopt from Korea.

Since 1955 over 100,000 Korean children have been adopted into US families, and the agency which grew out of the Holt's initial work, now called Holt International Children's Services, has been involved in 30 to 40 percent of these adoptions. Holt currently places about 300 Korean adoptees per year, and hundreds more from China and from programs in Bulgaria, Ecuador, Guatemala, Haiti, India, Mongolia, Philippines, Romania, Thailand, Uganda and Vietnam.

The process of adopting through Holt's Korea program takes roughly 12–18 months from initial application to bringing home the adoptee. The major steps include filing an application, participating in the home study assessment, attending adoption education classes, passing the criminal background check, being matched with an adoptee, the adoptee flying to the US, and legally adopting the child in family court. This is an extensive and thorough process requiring numerous meetings with adoption agency personnel and numerous exchanges of documents.

In part due to US and South Korean law, adoptive parents must meet several criteria including a minimum family income and being married for three years or longer.[1] US law requires that family income be 125 percent of the poverty level. (The data contain many families near this threshold.) Korean law requires that the adoptive parents be between the ages of 25 and 45 at the time of application processing and have no more than four children in their current family.

Within the Korea program and conditional upon being qualified to adopt, children are matched to families on a first come, first served basis. Thus it is the timing of when applications are completed that creates the matching of parents to children,

1. Information on Holt's policies and assignment process is provided from their website www.holtintl.org and my interviews with Holt officers.

rather than any matching of parent and child characteristics. This is what results in quasi random assignment of adoptees to families. Precisely which adoptee goes to which family is determined by fairly "random" factors such as whether it takes the parents eight weeks versus nine weeks to get their home study completed or to have their recommendation letters mailed in. Small differences in motivational levels would have small effects on how quickly the process is completed, but these differences in efficiency are uncorrelated with any characteristics of the adoptee. In my analysis I include cohort dummies in case parent and child characteristics co-vary systematically over time.

Parents are not given the opportunity to specify gender or anything else about their future adoptee. The one exception to this rule is that families with all boys or all girls were allowed to request a child of the opposite gender.[2] In practice, those who were eligible to request girls frequently did so. This does not present a problem for this study since I condition on adoptee gender in every specification. The only other opportunity parents have to specify a preference is to indicate that they would be open to adopting a child with special needs or a disability. I exclude all such adoptions from the sample.

Holt Children's Services of Korea, a separate organization from Holt International Children's Services, maintains a network of foster homes in Korea. When Korean mothers (or families) are forced through life circumstances to give up a child for adoption, the mother (family) will frequently bring the child to Holt's facility in Seoul or one of the eleven branch offices.[3] Holt places the child in one of its foster homes to await adoption. Currently the majority of children given up for adoption in Korea are born to unwed mothers. During the 1960s and 1970s when the adoptees in the study were placed, some of the relinquishments were due to unwed motherhood but others were due to poverty and the family's inability to care for the child.

The physical process of matching of adoptees to families is quite simple and as noted above uses a queuing system which

2. Even this exception was recently eliminated due to the overwhelming excess demand for girls.

3. During the 1970s it was common for the mother to relinquish the child into an orphanage. Holt Korea had a network of contacts with orphanages and would place children from these orphanages into US families.

effectively randomizes children to families.[4] Once Holt has a completed application file and has certified that the parents are qualified to adopt, the file is added to a small stack of other such applications completed that week. Once per week the stack of roughly 5–10 completed applications is sent to Holt Children's Services of Korea. Holt Korea receives the applications and assigns any children in its system to these prospective adoptive families on a first come first served basis. If no children are available at a given moment, then Holt Korea holds the file and waits for the next available child. From the point at which the child is assigned to an adoptive family, it takes about 4.5 months for the child to come home. I provide evidence below that the child's weight in infancy and other pre-adoption characteristics are uncorrelated with adoptive parent characteristics such as family income, parental education etc.

I.B. Relation to the Literatures on Adoption and Nature and Nurture

Psychologists and sociologists have long used adoption data as a way to examine the effects of family environment while (hopefully) controlling for the potentially confounding effects of genes or other prenatal factors which are likely strongly correlated with environment. The literature has focused mostly on estimating the heritability of IQ, as in Scarr, and Weinberg [1978], and personality traits as in Loehlin, Horn, and Willerman [1982, 1987, 1994], and Plomin, Defries, and Fulker [1988, 1994], and health outcomes like alcoholism or depression.[5]

As Jenks [1972] points out, studying IQ and other test scores is potentially very different than studying economic outcomes. I build on the work of a handful of papers which look at the effects of adoptive family environment on educational attainment including Teasdale, and Owen [1984], Lichtenstein, Pedersen, and McClearn [1992], and Scarr, and Weinberg [1994]. My value added relative to these papers is both the quasi-random assign-

4. In the 1970s, Holt and Holt Korea had no information about the birth parents which means that any matching based on birth parent characteristics would have been physically impossible anyway. For a small number of cases (99) Holt Korea estimated the birth mother's age but did not use that data for matching. I use the data on birth mother's age in one of several tests for random assignment.

5. See Bouchard, and McGue [1981] and Loehlin [1989] summaries of the very large IQ literature.

ment of adoptees into families and the much larger sample sizes in the Holt data.[6]

A series of recent papers in economics including Björklund, Lindahl, and Plug [2006], Sacerdote [2002], Das, and Sjogren [2002], and Plug, and Vijverberg [2003] looks at the transmission of income and education from birth and adoptive parents to adoptees and from parents to nonadoptees. The goal of this literature is to ask what portion of the transmission of income and education comes from nature (the birth parents), from nurture (the adoptive parents), and in the case of Björklund, Lindahl, Plug (BLP) the interaction of the two. The latter paper has by far the largest data set in that it uses the census of Swedish adoptees placed during 1962–1966. All of the existing work relies on an implicit or explicit assumption of random assignment of children to adoptive families. This assumption is necessary in order for the effects from adoptive family environment to be estimated without bias from the matching of children to parents.

There is also a literature in economics which uses twins data to separate out nature and nurture effects on educational attainment, income and obesity. A series of papers including Taubman [1989], Behrman, and Taubman [1989] and Behrman, Rosenzweig, and Taubman [1994] use comparisons of identical and fraternal twins and their offspring along with the behavioral genetics (BG) model to identify the nature and nurture components of these outcomes. However, Goldberger [1978] points out a number of severe limitations to the BG approach.

I depart from the existing economics literature on adoption in four important ways. First, the mechanism by which Holt assigns children to families is known and is effectively random. I provide empirical evidence as well as institutional detail on this point. Second, I use the traditional behavioral genetics model to arrive at explicit estimates of the relative importance of nature and nurture in explaining variance in a variety of outcomes. Third I have a wider range of outcomes than was available in previous economic studies and thus can provide a comparison between nurture's effect on "social" versus labor market outcomes.

Finally, I calculate treatment effects on child outcomes from

6. For instance, the numbers of adoptive sibling pairs in these three existing papers are 27, 61, and 59 respectively. Other existing papers which examine adoptee's educational attainment using a different methodology are Teasdale, and Owen [1986] and Maughan, Collishaw, and Pickles [1998].

being assigned to a small, high education family.[7] The treatment effects framework requires significantly fewer assumptions than a more structural approach like the BG framework. I focus on small, high education families because these two family characteristics appear to be the most correlated with adoptee outcomes and may indicate something about the quantity and quality of parental attention the adoptees receive. For certain outcomes, assignment to a small high education family has an effect similar in size to that of a one standard deviation change in the index of family environment implied by the BG model.

II. Empirical Frameworks

II.A. Variance Decomposition

My first empirical approach is a nature-nurture variance decomposition via the standard behavioral genetics (BG) model. This exercise provides an estimate of the importance of nature and nurture in explaining the variation in child outcomes. Suppose that child outcomes (Y) are produced by a linear and additive combination of genetic inputs (G), shared (common) family environment (F) and unexplained factors, which the BG literature often calls non-shared or separate environment, (S). This implies that child's educational attainment can be expressed as follows

$$\text{Child's years of education } (Y) = G + F + S \tag{1}$$

The strong assumptions here are that nature (G) and shared family environment (F) enter linearly and additively. To get a variance breakdown one generally further assumes that G and F are not correlated for both the adoptees and non-adoptees.[8] Taking the variance of both sides yields:

$$\sigma_{Y}^{2} = \sigma_{G}^{2} + \sigma_{F}^{2} + \sigma_{S}^{2} \tag{2}$$

7. By "treatment effect" I mean the casual difference in outcomes that results from a child being assigned to one type of family versus another. Holt is of course assigning children to a range of families which I aggregate into discrete treatment groups for this part of my empirical work.

8. This assumption can be justified for the Holt adoptees on the basis of quasi random assignment of children to families. Environment and genes are surely correlated for the non-adoptees, so on the surface this would seem like an indefensible assumption. One of the referees informs me that behavioral geneticists think of G as representing both the direct effects of genes *and* the effects of gene environment correlation. This is important for interpreting the variance breakdown.

Dividing both sides by the variance in the outcome (σ_Y^2) and defining $h^2 = \sigma_G^2/\sigma_Y^2$, $c^2 = \sigma_F^2/\sigma_Y^2$, and $e^2 = \sigma_S^2/\sigma_Y^2$ yields the standard BG relationship:

$$1 = h^2 + c^2 + e^2 \tag{2a}$$

The variance of child outcomes is the sum of the variance from the genetic inputs (h^2 or heritability), the variance from family environment (c^2) and the variance from non-shared environment (e^2), that is, the residual. From this starting point, a variety of variances and covariances of outcomes can be expressed as functions of h, c, and e. The sample moments can then be used to identify these underlying parameters. For example, if one standardizes Y, F, G, S to be mean zero variance one, the correlation in outcomes between two adoptive siblings equals $\mathrm{Corr}(Y_1,Y_2) = \mathrm{Cov}(Y_1,Y_2) = \mathrm{Cov}(F_1,F_1) = \mathrm{Var}(F_1) = c^2$.

The correlation in outcomes between two nonadoptive siblings equals $\mathrm{Corr}(Y_1,Y_2) = \mathrm{Cov}(G_1 + F_1 + S_1,\ G_2 + F_2 + S_2) = \mathrm{Cov}(G_1 + F_1,\ \tfrac{1}{2}G_1 + F_1) = \tfrac{1}{2}h^2 + c^2$. This assumes that nonadoptive siblings share half of the same genetic endowment and the same common environment (See Plomin et al. [2001] for a discussion). Thus one can recover the full variance breakdown (h^2, c^2, e^2) from just the correlation among adoptive and biological siblings. Notice that h^2 = twice the difference in correlations in the outcome between the adoptive and biological siblings. Given the decomposition I calculate how much one would expect a child's outcome to change given a one standard deviation change in the index of family environment, F. This quantity is $c \times \sigma_Y$.[9]

It is possible that my data exclude some critical (low) level of family environment which could be altered to deliver a larger percent of variance apportioned to shared family environment or larger treatment effects than those found here (See Turkheimer et al. [2003]). Stoolmiller [1999] points out that c^2 could significantly underestimate the fraction of variation explained by nurture if there is some restriction in the range of family environments observed. In practice the variance of family environment in the Holt data is as large as the variance of family environment observed in the US population. For example in the Holt data the standard deviations for mother's years of education, college status, and family income are 2.45 years, 49.9 percent, and $23,600 respectively. Using the Na-

9. By definition the r-squared from a regression of Y on $F = c^2 = \sigma_{\mathrm{yhat}}^2/\sigma_{\mathrm{y}}^2$, so $c \times \sigma_{\mathrm{y}} = \sigma_{\mathrm{yhat}}$.

tional Longitudinal Survey of Youth 1979 (NLSY79) data, weighted to represent the US population in 1979, the standard deviations for mother's education, college status and family income are 2.50 years, 31.7 percent, and $14,216. The Holt data do contain low income and low education families, even though the means of these two variables are significantly above US averages.

I also use Census data to compare the distribution of Holt adoptive family income at the time of adoption to that of all married, two parent families with children in the US in 1980. Family income for the latter group is calculated from the Individual Public Use Micro Sample (IPUMS) Census data. Contrary to common perception (likely based on current adoptive families), the adoptive families in the sample are not universally high income families. Families with less than $10,000 of annual income are significantly underrepresented in the Holt data, but such families still represent 25 percent of the Holt sample, versus 45 percent for US families with children in 1980. Sixty percent of the Holt families have income of $25,000 or less versus 73 percent for US families with children.

II.B. Treatment Effects

I also estimate the treatment effect on adoptee outcomes from being assigned to a particular family type. Interpreting these treatment effects as causal requires only that assignment to treatment group is quasi random. I define three different types of adoptive families based on their observables. Type one are high education, small families, meaning there are three or fewer children total *and* both parents have four years of college. Adoptees in such families comprise 27 percent of the sample. Type three families (12 percent of the adoptees) are those in which *neither* parent has four years of college *and* there are four or more children in the family. Type two families are the set of all other families not in either of the extreme groups. I calculate the treatment effects from assignment to type one versus three (high education, small vs. lower education large) and type two versus three.

To do this I take the set of adoptees in my sample and run regressions of the following form:

$$(3)\quad E_i = \alpha + \beta 1 * \mathrm{T1}_i + \beta 2 * \mathrm{T2}_i + \beta 3 * \mathrm{Male}_i + \boldsymbol{\gamma} * \mathbf{A_i} + \boldsymbol{\rho} * \mathbf{C_i} + \varepsilon_i$$

where E_i is educational attainment for child i, $\mathrm{T1}_i$ is a dummy for being assigned to a family of Type 1, $\mathrm{T2}_i$ is a dummy for being assigned to a family of type 2, $\mathbf{A_i}$ is full set of single year of age dummies, and $\mathbf{C_i}$ is a full set of cohort dummies.

The less educated larger adoptive families are the omitted category. The cohort dummies are included since assignment to treatment group is quasi random within the time period during which the family applied to adopt through Holt. In other words, child and family characteristics might vary over time in a non-random way. Cohort is defined as the year in which the child initially entered the Holt system in Korea. The age dummies are an additional control for the fact that outcomes like educational attainment vary with child age. Age and cohort are not perfectly collinear since there is some modest variation in age at adoption. (See summary statistics below.) The gender dummy is included because in a limited number of cases adoptive families are able to request the adoptee's gender. And like age dummies, the gender dummy improves precision on the estimated treatment effects by removing additional variation that would otherwise end up in the error term.

Due to quasi random assignment, $\beta 1$ can be interpreted as the causal effect of assignment to a high education small family, relative to assignment to a less educated large family.[10] I report results for both comparisons. Of course, the causal effect need not work directly via parental education or family size since other important environmental factors vary across family types. These factors could include income, parental attention, school quality neighborhood quality, etc. I defined family types using parental education and family size because these are the two observables that are most strongly correlated with child outcomes. And defining treatment groups in this way delivers treatment effects on educational outcomes that are similar in magnitude to a one standard deviation move in the index of shared family environment.

II.C. Estimation of Transmission Coefficients

Most studies of intergenerational correlations in economics focus on transmission coefficients in which the child's outcome is regressed on the parent's outcome. See Solon [1999] or Bowles,

10. Without random assignment, $\beta 1$ represents an unknown mix of treatment effects plus selection into the family (treatment group). This is why previous adoption studies by economists (including my own) generally avoid using causal or treatment effects language, and instead focus on estimating transmission coefficients.

Gintis, and Groves [2005] for a review. In order to provide comparability between my results and those in the existing literature I also calculate transmission coefficients for a variety of outcomes. For the adoptees this means running regressions of the following form:

$$(4) \qquad E_i = \alpha + \delta 1 * E_{\mathrm{M}_i} + \beta 3 * \mathrm{Male}_{\mathrm{i}} + \boldsymbol{\gamma} * \mathbf{A_i} + \boldsymbol{\rho} * \mathbf{C_i} + \varepsilon_i$$

where $E_{\mathrm{M}i}$ is adoptive mother's years of education and the other variables are as above. Again, the quasi random assignment ensures that there is no correlation between the child's initial health or genetic endowments and adoptive mother's education. This allows me to obtain an estimate of δ1 that is not biased by selection of adoptees into families. δ1 is the transmission that takes place purely through nurture and not through genes or pre-natal environment. For the nonadoptees I run analogous transmission regressions of the form:

$$(4a) \qquad E_j = \alpha + \delta 2 * E_{\mathrm{M}_j} + \beta 3 * \mathrm{Male}_{\mathrm{j}} + \boldsymbol{\gamma} * \mathbf{A_j} + \boldsymbol{\rho} * \mathbf{C_j} + \varepsilon_i$$

where the nonadoptees are indexed by j and M_j simply represents mother's education (not adoptive mother's education.) This yields an estimate of the transmission of education (outcomes) from parents to children when there is a genetic connection between the parent and child. A comparison between δ1 and δ2 is an estimate of how much of the transmission of education (outcomes) works through nurture, as opposed to through nature and nurture combined.

III. Data Description

Holt and I collected data on adoptive parents and their children using Holt records and a mail in survey.[11] A copy of the survey is included as Appendix III in Sacerdote [2005].[12] The survey asked parents for information on their education, occupation, income and health, where the latter includes height, weight, smoking and drinking status. We also asked the parents questions on the children's health, education, and income. We collected basic demographic outcomes for the children including marital status and number of children. We sent a pilot survey to

11. The effort required extensive work from Holt officers and employees and from a team of research assistants at Dartmouth.
12. This working paper is available at www.dartmouth.edu/~bsacerdo.

1,000 of the families. We then sent a main mailing to an additional 2,500 families. We then sent surveys to a subset of 653 of the children (both adoptees and nonadoptees) to measure the degree to which parents and children gave the same answer when asked about the child's outcome. Finally we sent 400 follow up surveys to a random subset of the parents who did not respond in the main mailing. The purpose of the follow-up was to allow us to ask whether non-response is correlated with either child outcomes or family background.

Parents were eligible for inclusion in the survey if they adopted a child through Holt's Korea program during 1970–1980, making the children ages 24–34 in 2004 when the survey was run. There were roughly 7,700 such families who met this criterion and as mentioned above we sent the survey to a random sample of 3,500 of these families.

Holt maintains electronic records with some basic pieces of information such as name, address, and adoptees' names and ages for each of the adoptive families. Whenever Holt has contact with a family they update the relevant address in their database. Contact may occur due to a family's use of Holt's post-adoption services, a family's subscribing to Holt's monthly magazine, or because of a donation to Holt. In addition, Holt contracts with a direct mail company to keep the addresses as accurate and up to date as possible. This is done in part by matching on exact names using US phone directories.

In the pilot and main mailing, our cover letter promised respondents a check for $50. This was paid immediately upon receipt of a completed survey. The survey of the children was conducted in a similar manner and also had an incentive payment of $50. For the follow up survey to nonrespondents we used US Priority Mail envelopes (to make the envelope more noticeable) and we offered $75.

Table IX in the Appendix shows the sample sizes and response rates for the various mailings. The main mailing went to 2,500 adoptive families. We received back 851 completed surveys for a response rate of 34 percent. We resurveyed 400 of the nonrespondents and had a 35 percent response on the resurvey. While neither response rate is terribly high, the resurvey data plus the complete data in Holt records allow me to examine the possible severity of nonresponse bias. In Sacerdote [2005] I provide a detailed analysis of nonresponse bias. I show that adoptee outcomes are not statistically significant predictors of whether the parents responded to the original mailing versus the follow-up mailing. This is some evidence against a story in which only parents of "successful" adoptees respond.

I use the administrative data in Holt records to ask whether parental characteristics predict non-response and report the results below in Table X in the Appendix. Parental characteristics do have modest power to predict nonresponse, though the estimated coefficients are small and in opposing directions. An additional year of father's education raises the probability of response by 1.4 percent, but a 10 percent increase in family income would decrease the probability of response by 1 percent. Since there is some evidence that response is correlated with family background, in all of the estimates below I attempt to correct for nonresponse bias by using Wooldridge's [1999] inverse probability weighting.[13]

III.A. Evidence of Random Assignment

The description of the adoption process in section II explains why assignment to families is effectively random conditional on the adoptee's cohort. Here I provide statistical evidence that adoptee and parent pre-treatment characteristics are indeed uncorrelated. Table I is calculated using data from Holt's records and includes all families to whom we sent surveys, whether or not they responded. Each column is a separate regression. I regress pre-treatment characteristics of the adoptee on pre-treatment characteristics of the adoptive family. The dependent variables are the adoptee's age at arrival in the US, weight upon entering the Holt system, height upon entering, and a dummy for male.[14] All regressions include dummies for adoptee age and cohort.

The right hand side variables are the log of family income, father's years of education, mother's years of education, and median income in adoptive family's zipcode. None of the family background characteristics are statistically significant predictors of adoptee age at arrival, height, weight or gender. The last row

13. Wooldridge demonstrates that one way to correct for nonresponse bias is to weight the observations by 1/[1-P(response)]. To estimate the probability of response, I use the fitted values from the probit in Table X of Appendix. Where it is impossible to calculate the fitted value (due to missing x's) I assign the observation the average response rate as the probability of response. The correction for nonresponse bias makes almost no difference in the estimates.

14. Male is usually a right hand side control to ensure quasi-randomization but I include it in column 4 as a dependent variable just to make the point that even the male dummy is uncorrelated with parent characteristics.

TABLE 1
EVIDENCE OF RANDOM ASSIGNMENT USING ADMINISTRATIVE RECORDS

	(1) Adoptee's age at arrival in US	(2) Weight when entered Holt system (lbs)	(3) Height when entered Holt system (inches)	(4) Adoptee is male	(5) Birth mother was married	(6) Birth mother's age at adoptee's birth	(7) Birth mother's highest grade completed
Log family income	0.001 (0.127)a	0.310 (0.258)	0.188 (0.225)	0.017 (0.022)	0.060 (0.081)	0.556 (1.784)	0.171 (0.968)
Father's years of education	−0.006 (0.010)	0.009 (0.043)	−0.019 (0.036)	0.006 (0.004)	−0.007 (0.015)	0.358 (0.376)	−0.094 (0.158)
Mother's years of education	−0.018 (0.015)	−0.037 (0.067)	0.014 (0.040)	0.003 (0.005)	0.001 (0.019)	−0.128 (0.545)	0.159 (0.172)
Log (median income in zip code in 1980)	0.145 (0.203)	0.201 (0.285)	0.149 (0.232)	−0.041 (0.029)	0.061 (0.111)	−3.422 (2.523)	−0.119 (1.106)
Observations	2158	2156	2157	2161	126	99	81
R-squared	0.143	0.704	0.640			0.232	0.345
F or χ^2 test for parental coeffs $= 0$	1.10	0.72	0.48	6.47	1.48	0.88	0.23
$p > F$: $p > \chi^2$	0.354	0.580	0.753	0.166	0.830	0.479	0.920

All data are from Holt records and include children of the families who responded and did not respond to the survey. I regress pre-adoption characteristics for the child on adoptive family characteristics. Regressions include dummies for the child's age and dummies for the year in which the child entered the Holt system. Information on birth mothers (columns (5)–(7)) is only available in a limited number of cases. The final rows show the F statistic for the joint significance of the four parental background variables. Columns (4) and (5) are probit regressions. For these, $\partial v/\partial x$ is reported and I use a chi-square test for the joint significance.

a Robust standard errors in parentheses: standard errors are clustered at the family level.

of the table shows the p-value for the joint significance of family background in predicting adoptee characteristics. As a group the family background variables are not significant in any of the regressions. In a very small number of cases Holt records contain data on the birth mother's marital status, age at adoptee's birth, and years of education. I use these as the dependent variable in columns (5), (6), and (7) respectively. And again I find no statistically significant relationship between birth mother characteristics and adoptive family characteristics.

Table II performs the same exercise as Table I, but within my analysis sample of Holt adoptees whose parents responded to the survey. The dependent variables are weight and height at the time of entry into the Holt system, the child's age at arrival in the US and a dummy for the adoptee being male. I include age and cohort dummies. There are more right hand side variables relative to the previous table since in the analysis sample I have all of the survey measures of adoptive family pre-treatment characteristics. For example, I now include mother's and father's heights, body mass indices and drinking status. Again, there is no statistically significant relationship between adoptee pre-treatment characteristics and adoptive family background characteristics. This can be seen in the last two rows of the table which report the F-statistic for the joint significance of the parental characteristics and the corresponding p-value.

III.B. Summary Statistics for the Analysis Sample

The survey collects outcomes for up to five children in the family. Fortunately for the purposes of sample size, most families had more than one child, and in many cases families had more than one Holt adoptee from Korea. Of the 1,197 families, 359 have two children, 329 have three children, and 230 have four children. Ninety-two families have six or seven children, but unfortunately we only collected information on five of the children in these large families. Only sixty-eight families have a single child, and that child is of course a Holt adoptee. In single child families, where there is exactly one Holt adoptee, 78 percent of the adoptees are girls. In families of two children, 80 percent of the children are adoptees and 63 percent are girls. In the larger families, 55–60 percent of the children are adoptees and about 55 percent are girls.

For the analysis sample, I limit the data to children who are currently ages 19–40. I dropped adoptees who were not adopted

TABLE II
EVIDENCE OF RANDOM ASSIGNMENT WITHIN ANALYSIS SAMPLE

	(1) Weight at initial social history (lbs)	(2) Height at initial social history (inches)	(3) Child's age at arrival	(4) Child is male
Mother's years of education	0.009 (0.088)	−0.045 (0.078)	−0.013 (0.012)	0.009 (0.007)
Father's years of education	−0.047 (0.073)	0.004 (0.069)	−0.000 (0.010)	0.001 (0.005)
Log parent's household income	−0.113 (0.276)	0.044 (0.243)	0.013 (0.041)	0.011 (0.022)
Mother's BMI	−0.032 (0.047)	−0.034 (0.047)	0.002 (0.005)	0.001 (0.003)
Father's BMI	−0.046 (0.037)	−0.061 (0.034)	−0.009 (0.006)	−0.002 (0.003)
Mother drinks	−0.000 (0.456)	0.043 (0.417)	−0.031 (0.059)	−0.008 (0.033)
Father drinks	0.298 (0.472)	−0.248 (0.426)	−0.050 (0.063)	−0.000 (0.035)
Mother's height (inches)	0.082 (0.070)	0.062 (0.061)	0.001 (0.008)	−0.001 (0.006)
Father's height (inches)	0.053 (0.063)	0.071 (0.056)	0.011 (0.007)	0.004 (0.004)
Constant	2.138 (5.993)	18.040 (5.437)**	0.507 (0.700)	0.636 (0.609)
Observations	989	1038	1040	1056
R-squared	0.188	0.320	0.266	0.062
F test, parental coeffs = 0	0.78	1.00	0.60	0.55
$p > F$	0.635	0.441	0.800	0.838

I regress child pre-treatment characteristics on adoptive family characteristics. This is the sample of adoptees whose families responded to the survey and for whom we have the relevant variables. All of the right hand side measures are taken from the survey data, but similar results obtain if we use parental education and income as reported in Holt records. All columns include dummies for child's age and for year of admission to Holt. The final rows show the F-test for the hypothesis that all the coefficients on the parental characteristics are zero. Robust standard errors in parentheses: standard errors are clustered at the family level.

* significant at 5%;

** significant at 1%.

through Holt's Korea program and adoptees who were listed as special needs children (since the latter are not randomly assigned). For the purposes of analyzing educational attainment, college status, and the child's family income, I further limit the sample to children ages 25–40. Of course to calculate data items like family size and percent girls in the family, I included all children in the family before limiting the sample on age, country of origin, Holt adoptee status, or special needs adoptee status.

Table III displays summary statistics for both the adoptees and nonadoptees. There are 1,650 adoptees and 1,196 nonadoptees. The adoptees are 30 percent male with an average age of 28. Fifty-eight percent of them have four years of college. Thirty-seven percent of the adoptees have four years of college from a college which is ranked by US News. This is a dummy variable which equals zero if the adoptee did not graduate from college or if the adoptee's college was not listed in the US News Rankings. Conditional on the adoptee attending (not necessarily graduating from) a US News Ranked College, the mean acceptance rate of the college was 70 percent. Reported annual family income for the adoptees is $49,000. Twenty-three percent of the adoptees smoke and 59 percent drink. These latter outcomes do not measure intensity of drinking and smoking but rather are dummy variables.

Since the survey was filled out by the parents, a natural question to ask is whether the parents report accurate answers for their children. I address this question in Table XI in the Appendix. Holt and I sent surveys to 653 of the children (two thirds of whom were adoptees) and received back surveys from 55 percent of those contacted. I was able to successfully match parent and child responses for about 229 adoptees and 93 nonadoptees.[15] Table XI in the Appendix shows the correlations between parent and child responses for these observations. For adoptee's years of education and college status, parent and adoptee responses have a correlation of .89 and .85 respectively. For adoptees height and BMI the correlations are .90 and .74 respectively. The only outcome with a correlation of less than .50 is the child's drinking status. This might mean that my estimate of family environment's ability to explain drinking behavior is biased upward or downward depending on

15. Because I don't have child names in the database, I had to match parent and child surveys on family id, gender, age and adoption status. I matched 90 percent of the surveys.

TABLE III
SUMMARY STATISTICS

Variable	Adoptees Obs	Adoptees Mean	Adoptees Std. dev.	Nonadoptees Obs	Nonadoptees Mean
For the children					
Child is male	1650	0.295	0.456	1196	0.622
Child's current age	1650	28.215	4.557	1196	32.292
Child's age at arrival in US	1640	1.369	0.826		
Child's years of education	1256	15.088	2.153	1051	15.914
Child has 4+ years college	1256	0.576	0.494	1051	0.713
Child graduated from a US News ranked college	1256	0.373	0.484	1051	0.469
Acceptance rate of college	725	0.697	0.174	598	0.672
Child's family income	1209	49.268	35.141	1025	64.239
Log (child's family income)	1209	3.648	0.740	1025	3.932
Child is married	1642	0.386	0.487	1156	0.633
Child's number of children	1562	0.520	0.905	1125	1.083
Child's BMI	1590	23.113	3.733	1130	24.007
Child is overweight	1590	0.240	0.427	1130	0.343
Child is obese	1590	0.061	0.239	1130	0.061
Child smokes	1649	0.230	0.421	1161	0.115
Child drinks	1635	0.593	0.491	1149	0.687
Child ever had asthma	1650	0.089	0.285	1188	0.089
For the parents					
Mother's years of education	1650	15.122	2.456	1180	15.285
Mother has 4+ years college	1650	0.528	0.499	1188	0.547
Father's years of education	1635	15.908	2.879	1171	16.272
Father has 4+ years college	1650	0.618	0.486	1179	0.673
Income at time of adoption (survey)	1624	32.472	23.646	1166	33.649
Income at time of adoption (Holt records)	1218	16817.780	9893.756	939	16675.520
Log family income (Holt records)	1216	9.591	0.534	935	9.581
Mother is overweight	1574	0.463	0.499	1132	0.436
Mother smokes	1629	0.033	0.177	1162	0.023
Mother drinks	1624	0.526	0.499	1161	0.571
Both parents have college degrees and family has three or fewer children	1627	0.273	0.446	1170	0.232
Neither parent has a college degree and family has four or more children	1627	0.128	0.334	1170	0.170

These are the means and standard deviations for the sample. Children are ages 19–40 in 2004. All adoptees are Korean American adoptees placed by Holt. Child's family income, years of education, college status are reported for children ages 25–40. Graduation from a US News Ranked College and Acceptance Rate are determined by matching the child's reported undergraduate institution with the 2004 US News Rankings. (Non-college graduates and graduates from unranked colleges are assigned a zero for US News Ranked Dummy.) Sample sizes vary due to differential reporting on the surveys and in Holt records.

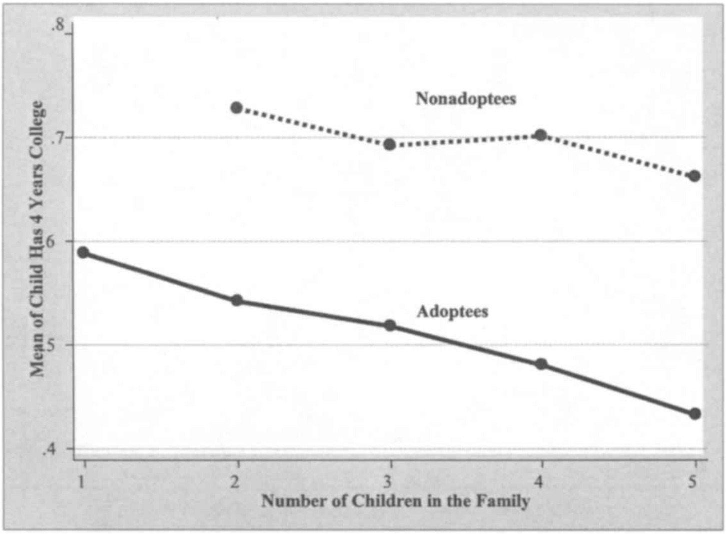

FIGURE I
Mean (College Attendance) By Family Size
Dashed line is for nonadoptees (higher line), solid line is for adoptees.

what sort of errors (or intentional misreporting) is involved. If parents are biased toward reporting that their adoptee has the same drinking behavior as their own, this would lead to an upward bias in the estimate of nurture's explanatory power.

IV. RESULTS

Figures I–III display some of the raw means graphically and foreshadow some of the key results. Figure I shows the probability of graduating from college by family size, separately for the adoptees and nonadoptees. Both groups show a steep decline in college graduation rates associated with each additional child added to the family. This fact survives all of the additional controls I can add (see discussion of Table VI below). Either there is a direct impact of family size on educational attainment, or as Black, Devereux, and Salvanes [2005b] suggest, family size proxies for something important and unobserved about the family.

Figure II shows the mean of child's years of education for both the adoptees and nonadoptees for each level of mother's

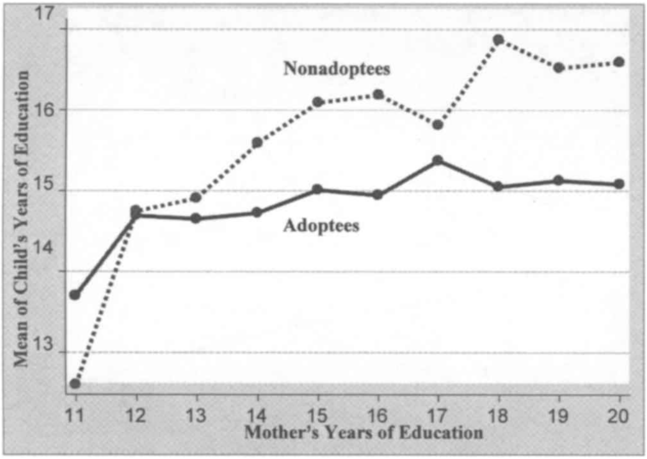

FIGURE II
Mean Child's Years of Education vs. Mother's
Dashed line is for nonadoptees. Solid line is for adoptees.

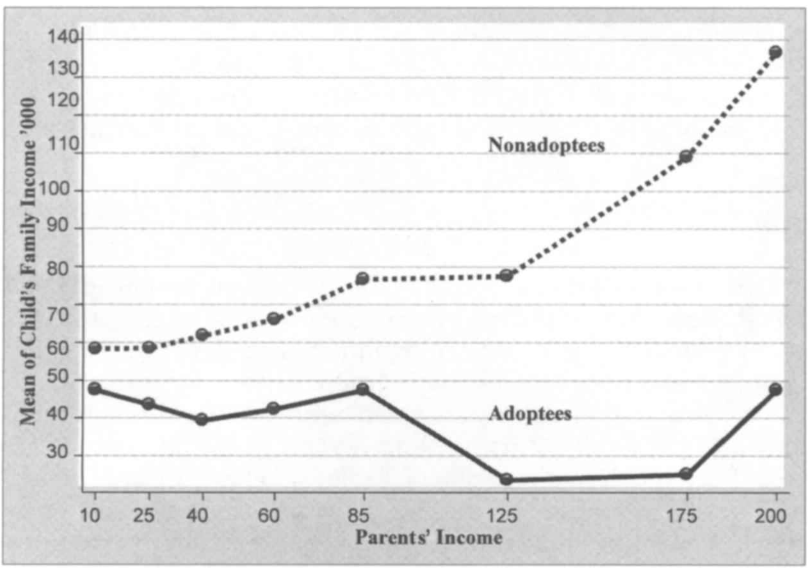

FIGURE III
Mean of Child's Family Income By Parents' Income at Adoption
Dashed line is for nonadoptees (higher line). Solid line is for adoptees.

education. Here one can see strong transmission of education from mothers to children. The upward sloping line is steeper for the nonadoptees relative to the adoptees. For both groups, the largest jump in average educational attainment is associated with the mother moving from 11 years of schooling to 12.

Figure III shows that income follows a rather different pattern. The graph displays the mean of child's family income (in thousands of dollars per year) by eight categories of adoptive family income at the time of adoption (survey measure). Income transmission is almost non-existent for the adoptees but strongly positive for the nonadoptees.

IV.A. Variance Decomposition

Table IV shows the correlations in outcomes among sibling pairs after removing age, cohort and gender effects.[16] For educational attainment, biological siblings have a correlation of .34 which is 2.4 times larger than the correlation of .14 for adoptive siblings. In contrast drinking behavior is almost as correlated for adoptive siblings as for biological siblings. Marital status is actually slightly more correlated for the adoptive siblings than the biological siblings with correlations of .08 and .05 respectively. These results are displayed in a scatter plot in Figure IV.

In Table V, I use the behavioral genetics framework to translate these correlations into the percent explained by nature, shared family environment and the residual (i.e. non-shared environment). Of the variation in college graduation status, 13.5 percent can be explained by family environment, 41 percent by nature, and 46 percent by non-shared environment. Variation in years of education has a similar breakdown at 16 percent family environment, 44 percent nature, and 40 percent non-shared environment.

Whether the percent of variation in educational attainment that is explained by family environment is high or low depends on one's priors. Following Duncan, Boisjoly, and Harris [2001], Jencks, and Brown [1979] and others, I show in the next section that a family environment share of 13 percent can lead to large effects on children's outcomes from changes in children's family environment.

16. All correlations in the table except for adoptive siblings' height and weight and nonadoptive siblings' marital status are statistically different from zero at the one percent level and most have p-values even smaller than one percent.

TABLE IV
CORRELATIONS IN OUTCOMES AMONG PAIRS OF ADOPTIVE SIBLINGS AND PAIRS OF BIOLOGICAL SIBLINGS

Outcome	Adoptive sibling correlation	Biological sibling correlation	N Adoptive	N Biological
Has 4 years of college	0.135	0.338	1360	578
Highest grade completed	0.157	0.378	1360	578
Family income	0.110	0.277	1314	554
Log (family income)	0.139	0.301	1314	554
Drinks	0.336	0.363	1903	640
Smokes	0.152	0.289	1938	654
Height	0.014	0.443	1910	646
Weight	0.044	0.273	1822	629
BMI	0.115	0.269	1821	629
Overweight	0.087	0.173	1821	629
Attended US News ranked school	0.249	0.416	1360	578
Acceptance rate of school	0.337	0.460	560	245
Married	0.076	0.048	1917	650
Number of children	0.105	0.203	1802	633

I form all possible pairs of siblings within the data set. I purge the outcome variables of variation due to age dummies, cohort dummies, and gender. I report the correlation in outcomes for adoptive sibling pairs and biological sibling pairs. Adoptive sibling pairs occur when either one or both of the siblings in a family are adoptees (and the adoptees do not share a biological mother or father). Biological sibling pairs are those that share a biological mother and father who are also the "nurturing" parents. All of the correlations are statistically different from zero at the 1 percent level except for height and weight among adoptive siblings.

My variance breakdown for years of education differs somewhat from the existing BG literature on IQ scores. Reviews of the adoption literature by Bouchard, and McGue [1981] or Plomin et al. [2001] suggest that for adults roughly half the variation in IQ can be explained by genetic factors and that family environment explains almost none of the variation. I find a significantly larger role for family environment in explaining educational attainment and this might be because I am examining a different outcome. In comparison to Behrman and Taubman's [1989] work on educational attainment in twins and their offspring which finds heritability of 81 percent, I find much smaller heritability and a larger percent explained by family environment. My estimates are much closer to those of Jencks and Brown [1979] which also uses twins data.

The few existing adoption behavioral genetics studies on educational attainment find a large range in percent of variation that is explained by family environment. My results are similar to

TABLE V
PROPORTION OF OUTCOME VARIANCE EXPLAINED BY HERITABILITY, SHARED FAMILY ENVIRONMENT, AND NON-SHARED ENVIRONMENT USING A SIMPLE BEHAVIORAL GENETICS MODEL

Outcome	Proportion explained by nurture (shared family environment)	Proportion explained by nature (heritability)	Unexplained portion (non-shared environment)
Has 4 years of college	0.135	0.406	0.459
Highest grade completed	0.157	0.443	0.400
Family income	0.110	0.334	0.556
Log (family income)	0.139	0.324	0.537
Drinks	0.336	0.055	0.609
Smokes	0.152	0.273	0.575
Height	0.014	0.858	0.128
Weight	0.044	0.458	0.498
BMI	0.115	0.308	0.577
Overweight	0.087	0.172	0.741
Attended US News ranked school	0.249	0.335	0.417
Acceptance rate of school	0.337	0.245	0.418
Married	0.076	−0.056	0.979
Number of children	0.105	0.196	0.699

I use the simple BG model described in the text to decompose the variance in each outcome into the portions attributable to genes (heritability), shared family environment, and non-shared family environment (i.e., the unexplained portion). See equations (2), (2A), and the paragraph that follows.

those of Lichtenstein, Pedersen, and McClearn [1992] who find that family environment explains 21 percent of the variance, and Scarr, and Weinberg [1994] who find an adoptive sibling correlation of .13. Teasdale, and Owen [1984] find an adoptive sibling correlation of .43. All three of these studies use completely different samples. Teasdale and Owen are examining a small sample of Danish siblings reared apart and Lichtenstein et al. are examining a small sample of Swedish twins reared apart. Differential selection of adoptees into families could explain the differences in results, or perhaps there is something fundamentally different about outcomes for siblings reared apart.

Perhaps the more interesting fact is how much the percent of variance attributable to nurture varies across different outcomes. When I consider graduating from a US News ranked college, family environment explains 25 percent of the variation, instead of the 14

TABLE VI
REGRESSION OF ADOPTEE OUTCOMES ON FAMILY CHARACTERISTICS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Child's years of education	Child has 4+ years college	Log child's household income	Child's BMI	Child overweight	Child drinks (yes/no)	Number of children
Mother's years of education	**0.097 (0.027)**a**	**0.023 (0.007)****	0.003 (0.010)	−0.074 (0.055)	−0.007 (0.006)	0.010 (0.006)	−0.017 (0.009)
Number of children	**−0.120 (0.050)***	**−0.026 (0.012)***	**−0.044 (0.017)***	0.106 (0.093)	0.011 (0.010)	0.001 (0.011)	0.016 (0.018)
Log parents' household income	−0.057 (0.098)	−0.001 (0.025)	0.027 (0.038)	−0.229 (0.197)	−0.031 (0.021)	0.008 (0.023)	**0.085 (0.035)***
Log (zip code income)	−0.133 (0.286)	0.045 (0.069)	−0.015 (0.104)	−0.232 (0.502)	−0.044 (0.060)	0.045 (0.070)	−0.179 (0.118)
Child is only adoptee in family	−0.058 (0.153)	−0.010 (0.037)	−0.026 (0.054)	−0.222 (0.301)	−0.042 (0.031)	0.026 (0.034)	−0.030 (0.058)
Fraction girls in family	0.078 (0.296)	0.042 (0.073)	−0.241 (0.104)*	−0.095 (0.626)	−0.060 (0.064)	0.013 (0.065)	−0.225 (0.105)*
Mother drinks	0.097 (0.138)	−0.009 (0.034)	0.016 (0.047)	−0.248 (0.267)	−0.016 (0.029)	**0.188 (0.030)****	−0.085 (0.046)
Mother's BMI	−0.028 (0.014)*	−0.005 (0.003)	−0.008 (0.005)	0.002 (0.024)	−0.001 (0.003)	0.001 (0.003)	0.003 (0.005)
Child is male	−0.633 (0.163)**	−0.145 (0.039)**	−0.285 (0.055)**	1.704 (0.283)**	0.192 (0.035)**	0.090 (0.032)**	−0.247 (0.049)**
Constant	15.412 (1.169)**		4.082 (0.450)**	26.717 (2.414)**			1.446 (0.478)**
Observations	1173	1173	1136	1138	1138	1532	1463
R-squared	0.081		0.124	0.080			0.220

I regress adoptee's outcome on a set of the adoptive family characteristics. Each column is a separate regression. Columns (2), (5), and (6) are probits and $\partial y/\partial x$ is reported. A full set of age dummies and dummies for year of admission to Holt are included in all columns.

a Robust standard errors in parentheses: I cluster at the family level.
* significant at 5%;
** significant at 1%.

percent of variation in graduating from any college. Variation in the selectivity of college attended is explained 34 percent by family environment and 25 percent by genetics. For drinking behavior, 34 percent of the variation is explained by family environment and almost none of the variation is explained by genetics.[17] My results on body mass index are consistent with several existing papers that demonstrate the high heritability of weight, notably Grilo, and Pogue-Geile [1991], Cardon [1994], and Vogler et al. [1995]. Variation in marital status appears to have a modest family environment component (8 percent) and no genetic component. My preferred interpretation of these results as a whole is that as one looks at more "social" outcomes such as drinking behavior or choice of college, family environment plays a larger role than it does in say the determination of years of education.

IV.B. Treatment Effects and Multiple Regression Results

Naturally understanding the causal mechanisms underlying the effects of family environment is at least as interesting as measuring the percent of variation explained. Because income, parental education, neighborhood quality, and many unobservables all covary, it is impossible to definitively separate out root causes. Nonetheless in Table VI, I use multiple regression to attempt to identify which aspects of family environment are the most important for the adoptees' outcomes. I regress various outcomes for the adoptees on mother's years of education, the number of children in the family, the log of family income at the time of adoption, log of median income in the zip code, a dummy for being the only adoptee, the fraction of girls in the family, and mother's body mass index, and drinking status.

A relatively clear pattern emerges. Even controlling for income and other aspects of family background, mother's education and the number of children in the family have a large effect on the adoptees' years of education and college status. Each additional child in the family reduces adoptees' educational attainment by .12 years. Mother's drinking status has a large effect on adoptees' drinking.[18] In contrast none of the income measures matter for

17. The existing literature finds that alcoholism is highly heritable (Cloninger, Bohman, and Sigvardsson [1981]). A plausible explanation for the difference in findings is that different processes are at work in the creation of social drinking versus alcoholism.

18. Using father's education and father's drinking status instead delivers similar coefficients to using the reports for the mother. (Results not shown).

adoptee's education or income. In addition to the specifications shown here, I tried all possible combinations of income from the survey (both at adoption and now), income from Holt records, and various measures of zip code income. One response to this negative result might be that the income measures are too noisy. However, this is not entirely persuasive because the family income measures are strongly correlated with each other and with outcomes for the nonadoptees.

Furthermore there is a literature associated with Mayer [1997] and Blau [1999] which argues that in the US, large changes in income result in only small increases in child test scores and educational attainment. These authors suggest that *other* aspects of family environment are much more important in determining child outcomes than is income per se. My results from the Holt data lead to the same conclusion.

One reasonable hypothesis to explain the results in Table VI is that the quantity and quality of parental attention matters a tremendous amount for the adoptees' outcomes. Each additional child in the family reduces the amount of parental attention available per child. Increases in birth order also have a negative but statistically insignificant effect on educational attainment for the adoptees.[19] Harris [1998] famously developed the thesis that parental attention is *not* a key input into child outcomes. One part of her evidence is the result that by adulthood, adoptee IQ is largely unaffected by adoptive family environment and she infers from this that effects on education and occupation may also be small. In contrast, this paper shows that adoptive family environment has large effects on economic outcomes.

Harris argues that peer and neighborhood influences are the primary determinant of why children turn out the way they do. However, Duncan, Boisjoly, and Mullan Harris [2001] point out that within family resemblance on outcomes (for achievement and delinquency) is much stronger than within school or within neighborhood resemblance. Their upper bound on the potential scope for peer and school influences is modest relative to the upper bound for the influence of genes and shared family environment. My results are consistent with Duncan et al. in that I do not find that zip code income, zip code education measures, urban density, or percent

19. Not shown. I tried defining adoptee birth order in the adoptive family in various ways including using actual birth years for all children in the family, and using the order of arrival in the household.

black have statistically significant impacts on adoptee outcomes.[20] In contrast characteristics about the adoptive family itself (namely parental education and family size) are strongly correlated with adoptee outcomes. To claim that the effects of family environment found here work strictly through peer effects (instead of parents) would require peer effects that are orders of magnitude larger than any of the modern peer effects studies like Hoxby [2000], Sacerdote [2001], or Angrist, and Lang [2004] that focus on isolating the causal impact of peers.

In Table VII I proceed to explicit estimates of treatment effects from assignment to a high education, small family via equation (3). I also present the effect from a one standard deviation change in the index of family environment using the behavioral genetics framework. In each row, Columns (1) and (2) show coefficients on dummy variables from a single regression. I regress the adoptee's outcome on a dummy for being assigned to a family in Group 2 (neither small, high education nor large less education) or to Group 1 (a high education family with three or fewer children). The omitted category consists of adoptees in Group 3, i.e., those with four or more children and in which neither parent has a college degree. These regressions include controls for adoptee gender, adoptee age, and adoptee cohort.

Column (3) reproduces the "effect" of assignment to a high education small family for the nonadoptees in the sample. This is to provide a basis for comparison and to show how effect sizes change when genes are covarying with family environment and parents are raising their biological child. Column (4) is the effect for the adoptees from a one standard deviation change in the index of family environment.

Assignment to a small, high education family relative to a lesser educated, large family increases educational attainment by .75 years and raises the probability of graduating from college by 16.1 percentage points. The probability of graduating from a US News Ranked college is increased by 23.1 percentage points relative to a mean of 37.3. These effects are similar to the effects of a one standard deviation increase in the index of family environment, using the variance decomposition implied by the behavioral genetics model. The latter approach yields effects of .85 additional years of

20. In the regressions reported in Table VI, I only include zip code income. But all zip code level measures have small and insignificant effects. Admittedly unlike the Duncan et al. paper, this may not be a particularly powerful test of whether neighborhoods matter.

TABLE VII
TREATMENT EFFECTS FROM ASSIGNMENT TO HIGH EDUCATION, SMALL FAMILY

	Treatment effect "middle group" of families vs. large, less educated	Treatment effect high education small family vs. large, less educated	Nonadoptees: High education small family vs. large, less educated	Effect from a 1 standard deviation change in family environment index
Child's years of education	0.314 (0.226)	0.749 (0.245)**	2.157 (0.264)**	0.845
Child has 4+ years college	0.060 (0.056)	0.161 (0.057)**	0.317 (0.031)**	0.179
Log child's household income	0.071 (0.081)	0.113 (0.089)	0.210 (0.089)*	0.263
Child four-year college ranked by US News	0.082 (0.052)	0.231 (0.060)**	0.365 (0.052)**	0.224
Acceptance rate of child's college	−0.007 (0.035)	0.016 (0.036)	−0.053 (0.032)	0.098
Child drinks (yes/no)	0.099 (0.050)*	0.178 (0.049)**	0.229 (0.041)**	0.280
Child smokes (yes/no)	0.013 (0.044)	−0.006 (0.048)	−0.075 (0.024)**	0.162
Child's BMI	−0.509 (0.460)	−0.941 (0.468)*	−0.929 (0.498)	1.224
Child overweight	−0.030 (0.047)	−0.077 (0.045)	−0.088 (0.048)	0.121
Child obese	−0.020 (0.023)	−0.044 (0.018)*	−0.037 (0.018)*	0.047
Child has asthma	−0.005 (0.028)	0.013 (0.031)	−0.005 (0.034)	0.085
Number of children	−0.070 (0.099)	−0.199 (0.103)*	−0.580 (0.132)**	0.267
Child is married	0.014 (0.050)	0.000 (0.056)	−0.092 (0.053)	0.123

I split the sample into three groups: High education small families are defined as those with three or fewer children in which both the mother and father have a college degree (Type 1). Twenty-seven percent of adoptees are assigned to such a family. Large lesser educated families are defined as those with four or more children and where neither parent has a college degree (Type 3). Thirteen percent of adoptees are assigned to such a family. The remaining families (which are either small or have a parent with a college degree) are Type 2. Column (1) shows the coefficient on the dummy for assignment to Type 2 relative to Group 3. Column (2) shows the coefficient on the dummy for assignment to Type 1 (small high education) relative to Type 3 (large less educated).

Column (3) shows this Type 1 versus 3 "effect" for the non-adoptees. In a each row, the effects in Columns (1) and (2) are estimated together with a single regression while Column (3) uses a separate regression. Column (4) shows the effect for the adoptees from a one standard deviation move in an index of shared family environment. This is calculated by taking the square root of the variance share explained by shared family environment in the previous table and multiplying by the standard deviation of the outcome variable: that is, $R \times \sigma_v = \sigma_{vhat}$ = predicted effect on the outcome from a one standard deviation change in an index of family environment. Standard errors are corrected for within family correlation (1 cluster by family).

education, a 17.9 percentage point increase in college graduation probability, and a 22.4 percentage point increase in the probability of graduating from a US News Ranked college. These effects from family environment strike me as quite large and I provide some context for this statement in the discussion section below.

The point estimates for the effect of a high education small family on child's family income (an increase of 11.3 percent) is also relatively large but the coefficient is not statistically significant. A one standard deviation change in the index of family environment is associated with a 26.3 percent increase in adoptee's family income.

There are also statistically significant treatment effects on drinking behavior. Assignment to a small, high education family raises the drinking rate by 17.8 percentage points. A one standard deviation change in the index of family environment is associated with a 28 percentage point change in the drinking rate. The literature on the relationship between drinking and income suggests a generally positive but non-linear relationship between own drinking and own income. Moderate levels of drinking are strongly positively associated with income, education and socio-economic status. Auld [2005] finds a 10 percent wage premium for moderate drinking relative to abstinence. My positive treatment effects on drinking from assignment to a small, high education family seem to be in the same spirit as the existing literature.

Assignment to a high education, small family reduces the adoptees' number of children (at the time of the survey). Adoptees of high education, small families have .20 fewer children relative to adoptees assigned to less educated large families. Some of the observed treatment effect might be delayed fertility as opposed to reduced fertility. Given that the average age of the adoptees is 28, I do not explore effects on completed fertility.

IV.C. Transmission Coefficients and Comparison to Other Adoption Studies

Table VIII shows results from my third empirical approach, namely calculating transmission coefficients from parents to children as in (4) and (4A). I include these since the economics literature generally measures parent-child connections using transmission coefficients. Transmission coefficients do not necessarily have a direct causal interpretation, but rather are a convenient and standard way to measure how changes in the child's outcome are associated with changes in the parental characteristic.

TABLE VIII
TRANSMISSION COEFFICIENTS FROM PARENTS TO CHILDREN FOR ADOPTEES AND NONADOPTEES

	(1) Adoptees' Transmission coefficient	(2) Nonadoptees' transmission coefficient
Years of education (mother to child)	0.089 (0.029)a**	0.315 (0.038)**
Has 4+ years college (mother to child)	0.102 (0.034)**	0.302 (0.037)**
Log household income (parents to child)	0.186 (0.111)	0.246 (0.080)**
Height inches (mother to child)	−0.004 (0.034)	0.491 (0.049)**
Is obese (mother to child)	0.003 (0.020)	0.108 (0.034)**
Is overweight (mother to child)	−0.026 (0.029)	0.174 (0.037)**
BMI (mother to child)	0.002 (0.025)	0.221 (0.045)**
Smokes (0–1) (mother to child)	0.132 (0.088)	0.108 (0.115)
Drinks (0–1) (mother to child)	0.210 (0.033)**	0.244 (0.038)**

I regress the child's outcome on the corresponding outcome for the mother (or in the case of income, the parents). Each cell is from a separate regression which also includes age dummies, dummies for year of admission to Holt, and a dummy for the child being male. For income and education regressions I restrict the sample to children ages 25+. For log (income), I attempt to correct for measurement error in parents' income by instrumenting for the survey measure of parents' income using the parents' income measure reported in Holt records.

a Robust standard errors in parentheses: I cluster at the family level.
* significant at 5%;
** significant at 1%.

For educational attainment, each additional year of mother's education is associated with .09 years of education for adoptees and .32 years for the nonadoptees.[21] The ratio of these two numbers may be a useful summary statistic: For the measured transmission of education from mothers to children, roughly 28 percent of this is working directly through nurture.

21. The income transmission coefficients are actually from the second stage of instrumental variables regressions. This is done in an attempt to clean up measurement error in income. I instrument for parental income as measured by the survey using parental income from Holt records and median income in the parents' zip code. I do not devote space to discussing the findings on income transmission for several reasons. First, I have only self reports of single years of income. This can greatly bias the estimated coefficients as discussed by Solon [1999]], Mazumder [2005] and others. Second, age of the parents and children matters a great deal too (Solon, and Haider [2006]). The adoptees and nonadoptees both have different average ages AND are significantly younger than the subjects in careful studies of income transmission.

Body mass index and height exhibit strong transmission from mothers to children for the nonadoptees but exhibit no transmission for the adoptees. Again, drinking has the appearance of a social outcome which is transmitted equally well to adoptees and nonadoptees. The coefficients are .21 and .24 respectively. In Figure V, I plot the adoptee transmission coefficients against the nonadoptee transmission coefficients. As with the sibling correlations in Figure IV, certain outcomes such as height, body mass index and years of education are significantly above the 45 degree line while drinking is almost directly on the 45 degree line.

Comparing results for the Holt data to results from other adoption data sets may tell us something about the degree to which sorting of adoptees into families biases the estimates of nurture's impact in existing studies. The four adoption datasets I consider are the Holt data, the Swedish data as analyzed by Björklund, Lindahl, and Plug [2006], the Wisconsin Longitudinal Survey as analyzed by Plug [2004], and the NLSY79 data as analyzed by Sacerdote [2002]. The adoptees in BLP's study are ages 35–37 in 1999. The adoptees in Plug's study are age 23 and older. For the NLSY data I use adoptees ages 28–36 in 1993.

For the adoptees, the Holt study and the Swedish (BLP) study yield similar transmission coefficients. The transmission coefficient for years of education is .089 for Holt and .074 for BLP. BLP's estimate of transmission of college status is somewhat larger than my estimate, but the estimates are within 1.2 standard deviations. A reasonable interpretation of the similarity of educational transmission coefficients in the Holt and Swedish samples is that any selection bias in the Swedish data is not particularly severe.[22]

In contrast the studies using the NLSY and WLS data find much larger coefficients for transmission of education from mothers to adoptees. These studies find coefficients of roughly .28. The most natural explanation for this difference is that there is strong positive (and unknown) selection of adoptees into adoptive families in those data sets. This would tend to bias the coefficient for the adoptees upward, and probably towards the coefficients for nonadoptees.

22. Obviously fundamental differences between the US and Sweden in the transmission process and differences in "restriction of range" among the SES of adoptive parents in the two samples could be offsetting some of the selection effects.

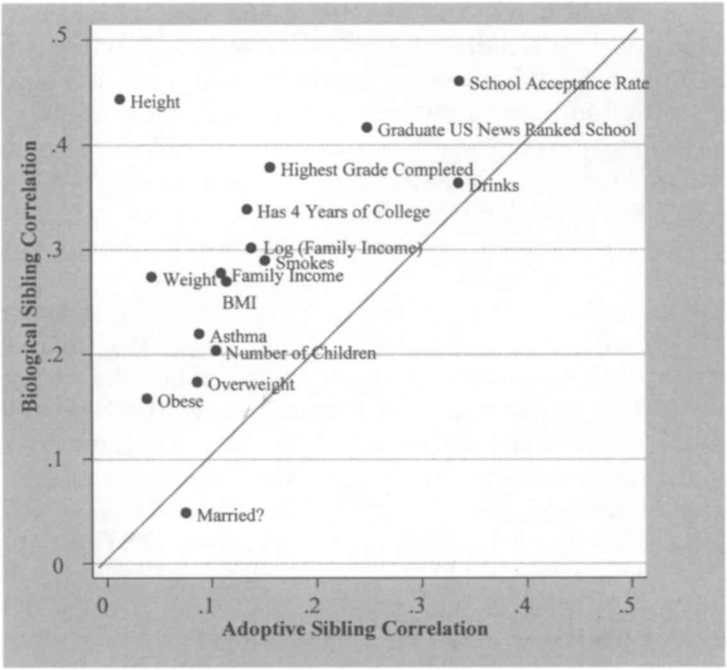

FIGURE IV
Comparison of Adoptive and Nonadoptive Sibling Correlations for Various Outcomes
This graph displays the results in Table IV.

V. Discussion and Conclusions

Analysis of the Holt data reveals several useful facts. First there are large treatment effects from adoptees being assigned to high education, small families. Adoptees in such families have an additional .75 years of education and are 16.1 percentage points more likely to graduate from college, relative to adoptees in larger, less educated families. The treatment effect on graduating from a US News ranked college is 23.1 percentage points. A one standard deviation change in the index of family environment causes an increase in years of education of .85, an increase in the college graduation rate of 17.9 percentage points, and a 26.3 percentage point increase in the rate of graduating from a US News ranked college.

Shared family environment can explain roughly 16 percent of the variation in educational attainment and 14 percent of the variation in the adoptee's family income. Genetic factors explain

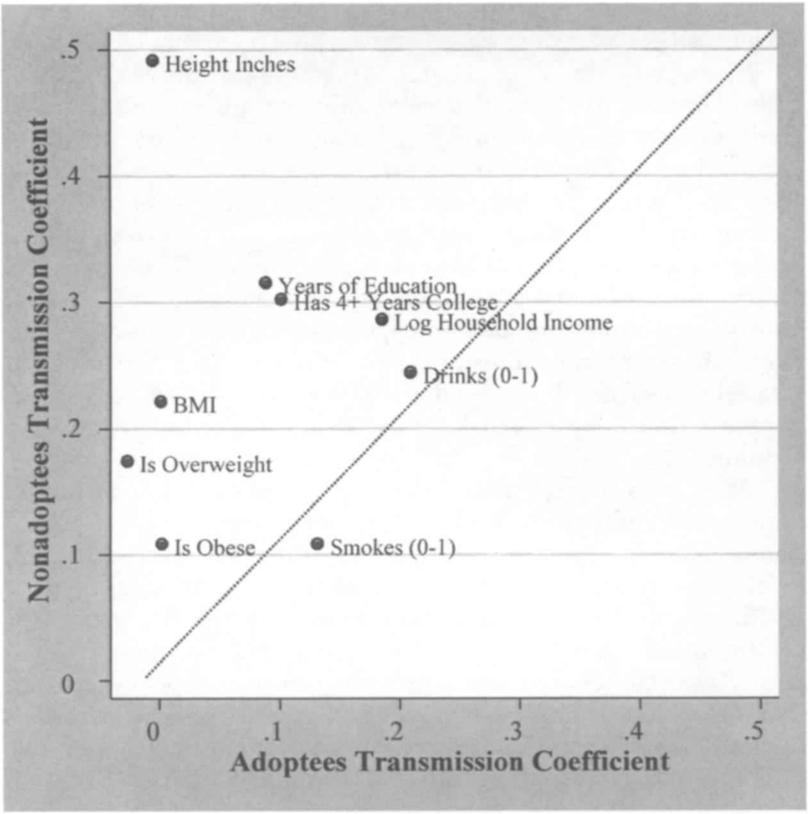

FIGURE V

Comparison of Coefficient of Transmission from Parent to Child

Graph shows coefficient from a regression of child's outcome on mother's outcome for adoptees and nonadoptees in the sample.

44 percent of the variation in educational attainment and 33 percent of the variation in income. In contrast, social outcomes like drinking, smoking, and marital status appear to be very nurture based. For drinking, family environment explains 34 percent of the variation while genes explain only 6 percent. The selectivity of the college attended is also strongly influenced by nurture.

Consistent with existing work on adoptees, shifts in family environment do not have a large influence on body mass index or probability of being overweight. Family environment explains almost none of the variation in weight (pounds) while genetics explain 46 percent. Mother's BMI is transmitted to adoptees with a coefficient of .002, but to nonadoptees with a coefficient of .221.

The study design does not allow me to make definitive statements about the causal mechanisms underlying the treatment effects found. However, I show that family size and parental education are much more strongly correlated with the adoptees' outcomes than are any of the measures of family income, zip code income, or other zip code characteristics. This finding suggests that the quality and quantity of parental attention may be two of the factors underlying the influence of family environment on outcomes, and that these factors matter more than income. Parental drinking is the factor most strongly associated with adoptee drinking, which of course suggests that adoptees pick up the behaviors they see modeled at home.

As Harris notes,[23] assignment of an adoptee to one family type versus another is one of the largest environmental interventions one might imagine, since family income, parental education, neighborhood peer quality and school quality are all shifted simultaneously from very early childhood onward. My estimated treatment effects provide a context for the possible effects from a large class of other environmental interventions or policy changes of interest. For example, Dynarski [2005] finds that large college tuition subsidies raise the rate of college graduation by 3 percent. This is roughly one fifth the effect of sending an adoptee to a high education small family, or roughly equivalent to a .17 standard deviation increase in an index of family environment.

Neal [1997], Evans, and Schwab [1995], Altonji, Elder, and Taber [2000] find that attending a Catholic school raises the probability of college going by 12–13 percent. This translates into perhaps a 6 percent effect on the college graduation rate if about half of these college entrants obtain a four year degree. Thus the Catholic schooling effect is roughly equivalent to a .34 standard deviation increase in the index of family environment.

The effects from a one standard deviation move in family environment may also provide a comparison basis for effects observed in other commonly observed environmental interventions such as altering a child's school peer group (Hoxby [2000],

23. 1998, pp. 260-261. This is similar in spirit to how Hernnstein, and Murray [1994]] attempt to tie the BG literature to possible effects from environmental interventions.

Angrist, and Lang [2004]), switching the child's school (Rouse [1998], Nechyba, and Vigdor [2003], Cullen, Jacobs, and Levitt [2005]), or switching the entire neighborhood *and* school as in the Moving to Opportunity experiment (Katz, Kling, and Liebman [2001], Kling, Ludwig, and Katz [2005], Ludwig, Duncan, Hirschfield [2001]).[24] The effect measured here from having a more educated mother would seem to place on upper bound on interventions that exogenously raise parental education as in Black, Devereux, and Salvanes [2005a] and Currie, and Moretti [2003]. I say this because the exogenous shock in the Holt data changes not only parental education but many other covariates.

The effects measured in the Holt data could useful for understanding black-white education (and possibly wage) differentials. The black-white gap in years of education is .78 years and the gap in the college completion rate is 15.4 percentage points. These numbers are equal to the effects of assigning an adoptee to a high education, small family relative to a large, less educated family. Or put another way, the black-white gap in education is equivalent to about a one standard deviation move in the index of family environment. Do we believe that the average environments faced by black and white children differ by as much one standard deviations of the family environment index in the Holt data? It certainly seems at least possible given the mountains of evidence on the environmental disadvantages faced by black children in the US.

In conclusion, the study extends our understanding of how differences in family environment lead to differences in outcomes for children. Rather than contradicting existing findings on the effects of environment, these results contribute to a consistent picture as to which outcomes are most affected by family environment, how much they are affected, and what some of the underlying mechanisms might be. Hopefully researchers will use the results here and the raw data to further our understanding of why children turn out the way they do.

DARTMOUTH COLLEGE AND NBER

24. I have in mind here a very specific set of family environment and schooling interventions. Namely ones that seek to influence child outcomes by raising family income, neighborhood quality, peer quality or school quality. I'm also thinking of those environmental interventions within the context of a rich country like the US.

APPENDIX

TABLE IX
RESPONSE RATES FOR THE MAILINGS

	Sent	Responded	Response rate
Pilot	1000	252	0.252
Main mailing	2500	851	0.340
Re-survey	400	141	0.353
Mailing to children	653	359	0.550

This shows the response rates for the three mailings to adoptive parents and the one mailing to adoptees and their siblings.

TABLE X
PROBIT FOR RESPONSE TO SURVEY

	Family responded W/O followup
Log family income	−0.093 (0.026)**
Father's years of education	0.014 (0.005)**
Mother's years of education	0.017 (0.006)**
Log median income in zip code in 1980	−0.016 (0.042)
Percentage in zip code with 4+ years college 1980	−0.056 (0.161)
Percent black in families' zip code 1980	−0.038 (0.111)
Observations	2138
F-test, parental coeffs = 0	40.43
$p > \chi2$	.000

I regress a dummy for responding to the survey on adoptive family characteristics as measured in the Holt records. The dummy is for responding in the original round of the survey, regardless of what the family did in the follow up round. I run a probit and report ∂_y/∂_x. Sample consists of all families who were sent a survey. Regression includes dummies for child's age and year of admission to Holt.

Standard errors in parentheses.

* significant at 5%;

** significant at 1%.

TABLE XI
CORRELATION BETWEEN PARENT AND CHILD RESPONSES FOR CHILD OUTCOMES

	Parents adoptees	Parents nonadoptees
Child's years of education	0.89; 228	0.78; 92
Child's college status	0.85; 228	0.83; 92
Child's family income	0.66; 210	0.86; 89
Child's height (inches)	0.90; 228	0.95; 92
Child's BMI	0.74; 220	0.76; 90
Child drinks (0−1)	0.48; 229	0.39; 91
Child smokes (0−1)	0.60; 229	0.77; 92
Child is married (0−1)	0.82; 229	0.73; 90

Child responses are obtained from a separate (smaller) sample of the children. Sample sizes are shown beneath each correlation.

References

Altonji, Joseph G., Todd E. Elder, and Christopher R. Taber, "Selection of Observed and Unobserved Variables: Assessing the Effectiveness of Catholic Schools," NBER Working Paper No. 7831, 2000.

Angrist, Joshua D., and Kevin Lang, "Does School Integration Generate Peer Effects? Evidence from Boston's Metco Program," *American Economic Review*, XCIV (2004), 1613–1634.

Auld, Christopher M, "Smoking, Drinking, and Income," *Journal of Human Resources*, XC (2005), 505–518.

Behrman, Jere R., and Paul Taubman, "Is Schooling 'Mostly in the Genes'? Nature–Nurture Decomposition Using Data on Relatives," *Journal of Political Economy*, XCVII (1989), 1425–1446.

Behrman, Jere R., Mark R. Rosenzweig, and Paul Taubman, "Endowments and the Allocation of Schooling in the Family and in the Marriage Market," *Journal of Political Economy*, CII (1994), 1131–1174.

Björklund, Anders, Mikael Lindahl, and Erik Plug, Intergenerational Effects in Sweden: What Can We Learn from Adoption Data?, *The Quarterly Journal of Economics*, forthcoming, 2006.

Black, Sandra, Paul J. Devereux, and Kjell G. Salvanes, "Why the Apple Doesn't Fall Far: Understanding Intergenerational Transmission of Human Capital," *The American Economic Review*, XCV (2005a), 437–449.

Black, Sandra, Paul J. Devereux, and Kjell G. Salvanes, "The More the Merrier? The Effect of Family Size and Birth Order on Children's Education," *The Quarterly Journal of Economics*, CXX (2005b), 669–700.

Blau, David M., "The Effect Of Income On Child Development," *The Review of Economics and Statistics*, LXXXI (1999), 261–276.

Bowles, Samuel, Herbert Gintis, and Melissa O. Groves, eds. *Unequal Chances: Family Background and Economic Success*, (Princeton: Princeton University Press, 2005).

Bouchard, T. J., and M. McGue, "Familial Studies of Intelligence: A Review," *Science*, CCXII (1981) 1055–1059.

Cardon, Lon R., "Height, Weight and Obesity," in *Nature and Nurture During Middle Childhood*, DeFries, John C., Robert Plomin, and David W. Fulker, eds. (Oxford, UK: Blackwell, 1994).

Cloninger C. R., M. Bohman, and S. Sigvardson, "Inheritance of Alcohol-Abuse—Cross-Fostering Analysis of Adopted Men," *Archives Of General Psychiatry* XXXVIII (1981), 861–868.

Cullen, Julie B., Brian Jacob, and Steven Levitt, "The Impact of School Choice on Student Outcomes: An Analysis of the Chicago Public Schools," *Journal of Public Economics*, LXXXIX (2005), 729–760.

Currie, Janet, and Enrico Moretti, "Mother's Education and the Intergenerational Transmission of Human Capital: Evidence from College Openings," *Quarterly Journal of Economics*, CXVIII (2003), 1495–1532.

Das, Mitali, and Tanja Sjogren, "The Intergenerational Link in Income Mobility: Evidence From Adoptions," *Economics Letters*, LXXV (2002), 55–60.

DeFries, John C., Robert Plomin, and David W. Fulker, *Nature and Nurture During Middle Childhood*, (Oxford, UK: Blackwell, 1994).

Dickens, William and James R. Flynn, "Heritability Estimates versus Large Environmental Effects the IQ Paradox Resolved," *Psychological Review*, CVIII (2001), 346–369.

Duncan, Greg J., Johanne Boisjoly, Kathleen M. Harris, "Sibling, Peer, Neighbor, and Schoolmate Correlations as Indicators of the Importance of Context for Adolescent Development," *Demography*, XXXVIII (2001), 437–447.

Dynarksi, Susan, "Building the Stock of College Educated Labor," NBER Working Paper No. 11604, 2005.

Evans, William N., and Robert M. Schwab, "Finishing High School and Starting College: Do Catholic Schools Make a Difference?," *The Quarterly Journal of Economics*, CX (1995), 941–974.

Goldberger, Arthur S., "The Genetic Determination of Income: Comment," *American Economic Review*, CXVIII (1978), 960–969.

Grilo, Carlos M., and Michael F. Pogue-Geile, "The Nature of Environmental

Influences on Weight And Obesity: A Behavior Genetic Analysis," *Psychological Bulletin*, CX (1991), 520–537.

Harris, Judith Rich, *The Nurture Assumption: Why Children Turn out the Way They Do*, (New York: Free Press, 1998).

Herrnstein, Richard J. and Charles Murray, *The Bell Curve: Intelligence and Class Structure in American Life*, (New York: Free Press, 1994).

Hoxby, Caroline M., "The Effects of Class Size on Student Achievement: New Evidence from Population Variation," *Quarterly Journal of Economics*, CXV (2000), 1239–1285.

Jencks, Cristopher, *Inequality: A Reassessment of the Effects of Family and Schooling in America*, (New York: Basic Books, 1972).

Jencks, Cristopher, and Marsha Brown, "Genes and Social Stratification;" in *Kinometrics: The Determinants of Economic Success Within and Between Families*, P. Taubman, ed. (New York: North Holland Elsevier, 1979).

Katz, Lawrence F., Jeffrey R. Kling, and Jeffrey B. Liebman, "Moving to Opportunity in Boston: Early Results of a Randomized Mobility Experiment," *Quarterly Journal of Economics*, CXVI (2001), 607–654.

Kling, Jeffrey R., Jens Ludwig, and Lawrence F. Katz, "Neighborhood Effects on Crime for Female and Male Youth: Evidence from a Randomized Housing Voucher Experiment," *The Quarterly Journal of Economics*, CXX (2005), 87–130.

Lichtenstein, Paul, Nancy L. Pedersen, and G. E. McClearn, "The Origins Of Individual-Differences in Occupational-Status and Educational-Level—A Study of Twins Reared Apart and Together," *Acta Sociologica*, XXXV (1992),13–31.

Loehlin, John C., "Partitioning Environmental and Genetic Contributions to Behavioral Development," *American Psychologist*, XCIV (1989), 1285–1292.

Loehlin, John C., Joseph M. Horn, and Lee Willerman, "Personality Resemblances Between Unwed Mothers and Their Adopted-Away Offspring," *Journal of Personality and Social Psychology*, XLII (1982), 1089–1099.

——, "Differential Inheritance of Mental Abilities in the Texas Adoption Project," *Intelligence*, XIX (1994), 325–336.

Loehlin, John C., Lee Willerman, and Joseph M. Horn, "Personality Resemblance in Adoptive Families: A 10-Year Followup," *Journal of Personality and Social Psychology*, LIII (1987), 961–969.

Ludwig, Jens, Greg J. Duncan, and Paul Hirschfield, "Urban Poverty and Juvenile Crime: Evidence from a Randomized Housing Mobility Experiment," *Quarterly Journal of Economics*, CXVI (2001), 655–680.

Maughan, Barbara, Stephen Collishaw, and Andrew Pickles, "School Achievement and Adult Qualification Among Adoptees: A Longitudinal Study," *Journal of Child Psychology and Psychiatry*, XXXIX (1998), 669–685.

Mayer, Susan E., "*What Money Can't Buy: Family Income And Children's Life Chances*," (Cambridge: Harvard University Press, 1997).

Mazumder, Bhashkar, "The Apple Falls Even Closer to the Tree than We Thought," in *Unequal Chances: Family Background and Economic Success*, Bowles, Samuel, Herbert Gintis, and Melissa O. Groves, eds. (Princeton: Princeton University Press, 2005).

Neal, Derek, "The Effects of Catholic Secondary Schooling on Educational Attainment," *Journal of Labor Economics*, XV (1997), 98–123.

Nechyba, Thomas, and Jacob Vigdor, "Peer Effects in North Carolina Public Schools," Mimeo, Duke University, (2003).

Plomin, Robert, John C. DeFries, and David W. Fulker, *Nature And Nurture During Infancy And Early Childhood*, (Cambridge, MA: Cambridge University Press, 1988).

Plomin, Robert, John C. DeFries, Gerald E. McClearn, and Peter McGuffin, *Behavioral Genetics,* 4th ed. (New York: Worth Publishers, 2001).

Plug, Erik, "Estimating the Effect of Mother's Schooling on Children's Schooling Using a Sample of Adoptees," *American Economic Review*, XCIV (2004), 358–368.

Plug, Erik, and Wim Vijverberg, "Schooling, Family Background and Adoption: Is it Nature or is it Nurture?," *Journal of Political Economy*, CXI (2003), 611–641.

Rouse, Cecilia E., "Private School Vouchers and Student Achievement: An Evaluation of the Milwaukee Parental Choice Program," *Quarterly Journal of Economics*, CXIII (1998), 553–602.

Sacerdote, Bruce I., "Peer Effects With Random Assignment," *Quarterly Journal of Economics*, CXVI (2001), 681–704.

——, "The Nature and Nurture of Economic Outcomes," *American Economic Review*, XCII (2002), 344–348.

——, "How Large are the Treatment Effects from Family Environment (Working Paper)," Mimeography, Dartmouth College, (2005).

Scarr, Sandra, and Richard A.Weinberg, "The Influence of Family Background on Intellectual Attainment," *American Sociological Review*, XVIII (1978), 674–692.

——, "Educational and Occupational Achievements of Brothers and Sisters in Adoptive and Biologically Related Families," *Behavior Genetics* XXIV (1994), 301–325.

Solon, Gary, "Intergenerational Mobility in the Labor Market," in *Handbook of Labor Economics, Vol 3*, Orley Ashenfelter, and David Card, eds. (New York: Elsevier Science, 1999).

Solon, Gary, and Steven Haider, "Life-Cycle Variation in the Association between Current and Lifetime Earnings," American Economic Review, XCVI (2006), 1308–1320.

Stoolmiller, Michael, "Implications of the Restricted Range of Family Environments for Estimates of Heritability and Nonshared Environment in Behavior-Genetic Adoption Studies," *Psychological Bulletin*, CXV (1999), 392–409.

Taubman, Paul, "Role of Parental Income in Educational Attainment," *American Economic Review*, LXXIX (1989), 57–61.

Teasdale T. W, and David R. Owen, "Heredity and Familial Environment in Intelligence and Educational Level—A Sibling Study," *Nature,* CCCIX (1984), 620–622.

——, "The Influence of Paternal Social-Class on Intelligence and Educational-Level in Male Adoptees and Non-Adoptees," *British Journal Of Educational Psychology,* CVI (1986) 3–12.

Turkheimer, Eric, Andreana Haley, Mary Waldron, Brian D'Onofrio, and Irving I. Gottesman, "Socioeconomic Status Modifies Heritability of IQ in Young Children," *Psychological Science*, XIV (2003), 623–628.

Vogler, G. P., T. I. A. Sorensen, A. J. Stunkard, M. R. Srinivasan, and D. C. Rao, "Influences of Genes and Shared Family Environment on Adult Body Mass Index Assessed in an Adoption Study by a Comprehensive Path Model," *International Journal of Obesity,* XIX (1995),40–45.

Wooldridge, Jeffrey M. "Asymptotic Properties of Weighted M-Estimators for Variable Probability Samples," *Econometrica*, CXVII (1999), 1385–1406.