

Schooling, Family Background, and Adoption: Is it Nature or is it Nurture?

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Abstract: When parents are more educated, their children tend to receive more schooling as well. Does this occur because parental ability is passed on genetically or because more educated parents provide a better environment for children to flourish? Using an intergenerational sample of families, we estimate on the basis of a comparison of biological and adopted children that about 65 to 80 percent of the parental ability is genetically transmitted.

1 Introduction

Many studies show that children raised by highly educated parents receive more schooling than children raised by less educated parents. However, the notion that education is persistent across generations does not necessarily imply that education itself is the driving factor behind this family connection. Other potential factors are inheritance of ability, more favorable academic environment, higher aspirations, or better access to financial resources.

The economics literature examines this family connection with models where the educational attainment of children is regarded as the outcome of a family decision making process that links parental resources and chil-

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dren outcomes through human capital investments. These models support the empirical observation that more family income, earned on average by highly educated parents, stimulate further schooling (Becker and Tomes, 1986; reviewed by Haveman and Wolfe, 1995).

Sociologists have presented considerable empirical and theoretical evidence on the relation between the incomes and education levels of parents and children. Their various theories reflect on ways that might determine educational mobility. Cultural reproduction theory, for example, claims that education serves as the main reproductive channel for intergenerational status transmission (Collins, 1971; Niehoff and Ganzeboom, 1996). Modernization theory, on the other hand, suggests that parental income and command over resources are responsible forces underpinning the intergenerational transfers (Blau and Duncan, 1967).

In their widely debated book *The Bell Curve* Herrnstein and Murray (1994) argue that it is ability measured as IQ that matters. Highly educated parents have more ability on average than less educated parents. If ability is transmitted from parents to children, education turns out to be persistent across generations. Furthermore, not only are high ability parents highly educated, they also generate more income. If family income matters for educational achievement, ability effects run through income as well. Altogether, Herrnstein and Murray claim that it is nature rather than nurture that explains educational persistence across generations.²

This paper aims to unravel the ability factors behind this family connection using the intergenerational mobility model of human capital proposed by Becker and Tomes (1986). We show how ability, family income and education move across generations, and we show what happens to mobility of human capital if we embrace the idea that part of ability is hereditary.

To fulfill this ambitious plan, we explore a unique US dataset, the Wisconsin Longitudinal Survey (WLS), that contains very detailed multigenerational information about households. Data collection started in 1957 on a group of 16 years old high school students in the American state of Wisconsin. Information was gathered about their IQ, family background, and so on. In 1964, 1975 and 1992 the same students were contacted again and information was collected about their school careers, labor market status,

²Herrnstein and Murray (1994) have been widely criticized by, to name a few economists, Ashenfelter and Rouse (1999), Cawley, Heckman and Vytalil (1998), Goldberger and Manski (1995), Korenman and Winship (1995). If we only consider the empirical analysis, the main gist of the critique is that IQ is an important but not a dominant factor in predicting economic and social success.

family conditions and the school careers of their children. To shed light on the importance of the heritability of ability, we use information whether these children are their parents' own offspring as opposed to adopted children. We shall further assume that ability is wholly determined by IQ. Plug, van Praag and Hartog (1999) already point to the fact that ability as such is only incompletely measured but for now it serves as an interesting starting point for the exercise to be developed in this paper.

Our empirical analysis consists of three parts. Firstly, we estimate a base model that focuses on the well-established fact of educational transfers between parents and children. The human capital estimates of this model do not suffer from ability bias as we include an explicit proxy for ability measured as IQ test scores. Secondly, we determine whether family income matters for human capital transmissions. Note that no clear answer is found by simply adding family income to the list of our variables since pure human capital and ability effects may run through income as well. What we do is we estimate that part of income that is arguably generated by luck and we include this variable in our analysis. We then track down the school performance of children whose parents experienced random income shocks to see whether income truly matters. Thirdly, we evaluate Herrnstein and Murray's hypothesis. We consider the mobility effects of ability and introduce a mechanism to disentangle persistence effects caused by nature and nurture.

Economists have studied ability determinants of educational attainment and found that smarter students likely obtain more schooling, but these studies have mostly skirted the nature/nurture debate. A few recent exceptions are Behrman and Taubman (1989), and Behrman, Rosenzweig and Taubman (1994) who use correlations between relatives and twins to decompose nature from nurture effects. Their models merely focus on inequality of opportunity from which they conclude that schooling is mostly in the genes.³ The present study has various advantages over former approaches. The first advantage lies in the level of abstraction. Former studies use variance decomposition to infer information on whether nature or nurture is the determining factor in describing inequality in human capital. This information is rather abstract as it only reflects relative contributions to R^2 . In contrast, we estimate which part of ability is inherited and which part can be attributed to the environment. In doing so we decompose ability effects in

³Goldberger (1979) argues that their framework puts the emphasis on genes rather than environment.

the more concrete form of regression slopes. The second advantage concerns the flexibility in the role of income. Our study does not treat income as an explicit environmental variable. Rather, it models ability transfers in a way that allows ability effects to run through income as well. The final advantage is one of focus. The economics literature thus far uses information on twins and relatives to isolate a genetic transmission mechanism. We apply information on adopted children to isolate the environmental transmission mechanism. Notice that the two models are complementary: both intend to describe the same intergenerational phenomena. Thus, it is interesting to have a well-developed parallel set of findings.⁴

The remainder of this paper is organized as follows. Section 2 introduces the model describing the relation between school choices and family background. In Section 3 we briefly discuss the econometric ramifications. Section 4 describes the data from the Wisconsin Longitudinal Survey in more detail. Section 5 presents and discusses our empirical findings. In Section 6 we examine the robustness of our nature and nurture estimates. Finally, Section 7 summarizes our conclusions.

The main conclusion of the paper is that parental ability measured as IQ is a dominating factor in explaining the children's school success. Yet, even if high ability parents do stimulate their children's human capital, a portion of the transmission channel runs through parental education and family income as well. Thus, if we decompose the ability transfers from parent to child into a genetic and environmental component, we find that about 65 to 80 percent of the ability effect relevant for school achievement is determined by nature. Nurture does not play a dominant role.

2 The model

The mobility of human capital is modeled akin to Becker and Tomes (1986), with the exception that this model considers the transmission of human capital instead of income. If t indexes generations, family income y_{t-1} is generated by human capital h_{t-1} , ability e_{t-1} and market luck u_{t-1} . This relation is written as

$$y_{t-1} = a_0 + a_1 h_{t-1} + a_2 e_{t-1} + u_{t-1} \quad (2.1)$$

⁴The idea to use adopted children to measure the difference between the environmental and genetic influence of family background is not new. Sociologists Scarr and Weinberg (1978) estimated the genetic component in IQ transfers to be 40 to 70 percent using a very small and selective sample.

Contrary to market luck u which is assumed not to be transmitted from parent to child, ability e transfers from parent to child through genes and culture. We assume the following relation

$$e_t = b_0 + b_1 e_{t-1} + v_t \quad (2.2)$$

where v is a non-structural component of ability. Based on maximizing behavior, parents invest in human capital of their children. As a result, family income and individual ability are the ingredients of the children's human capital function

$$h_t = c_0 + c_1 y_{t-1} + c_2 e_t + w_t \quad (2.3)$$

Like v , w is considered random variation. The disturbances u , v and w have zero means and are assumed to be temporally uncorrelated.⁵

Identification of the model requires data for several generations on a large number of families, all under constant conditions. To this end, we use a dataset with information on human capital of children and parents h_t and h_{t-1} , income of parents y_{t-1} , and parental ability e_{t-1} .

2.1 Intergenerational mobility of human capital

Intergenerational mobility literature shows persistently that children raised in highly educated families receive more schooling than children raised in less educated families. We address the educational mobility by combining equations (2.1) and (2.3). The resulting expression relates human capital of the children to ability and parental human capital

$$h_t = c_0 + a_0 c_1 + a_1 c_1 h_{t-1} + a_2 c_1 e_{t-1} + c_2 e_t + c_1 u_{t-1} + w_t \quad (2.4)$$

Because children's ability e_t is not available, we substitute (2.2) in (2.4) and arrive at the children's human capital relation

$$h_t = c_0 + a_0 c_1 + b_0 c_2 + a_1 c_1 h_{t-1} + (a_2 c_1 + b_1 c_2) e_{t-1} + c_1 u_{t-1} + c_2 v_{t-1} + w_t \quad (2.5)$$

Controlling for ability, parental human capital is transmitted to children through parental income $a_1 c_1$. Part of the ability transfers run through the same parental income channel $a_2 c_1$. The other part, $b_1 c_2$, is a direct ability effect on the formation of human capital.

⁵Goldberger (1989) speaks of mechanical rather than economic mechanisms when he discusses intergenerational transmission models. For our exercise to be developed in this paper we do not need the assumption that parents maximize their utility.

2.2 Intergenerational mobility of parental income

Both parental human capital and ability affect the human capital investment of children through family income, which is clearly seen when we combine (2.2) and (2.3) and we write down for today's generation

$$h_t = c_0 + b_0c_2 + c_1y_{t-1} + b_1c_2e_{t-1} + w_t + c_2v_t \quad (2.6)$$

Because high ability parents generate on average more income, there is collinearity between e_{t-1} and y_{t-1} , which means that the importance of parental income and ability *per se* cannot be obtained by means of direct estimation. An alternative way to identify these effects is to isolate that part of parental income that represents income out of "luck", namely u_{t-1} . If luck is identified, we are able to use luck as an instrument in (2.6) and shed light on the overall contribution of ability, e_{t-1} . Also, equation (2.5) allows us to estimate income effects directly through c_1u_{t-1} . Later on, Section 5 will explain the methodology of how we isolate income generated out of market luck.⁶

2.3 Intergenerational mobility of ability: nature or nurture?

In this paper we refer to cognitive ability whenever we discuss ability, and we use IQ test scores to measure it.⁷ The model clearly shows that ability matters. How much it exactly matters is extensively debated in the literature. Some argue that IQ is only a poor predictor of school performance (Cawley et al., 1996). Others claim that IQ is the driving force in explaining human capital accumulation (Herrnstein and Murray, 1994). The importance of ability transfers increases if IQ is thought to be hereditary.

This paper adds to this debate. It inserts new evidence on the importance of the heritability of IQ, evidence that is based on a novel approach. For parents and their biological children, ability transmissions run through both genetic and cultural channels. For adopted children, however, genetic transfers do not exist. Define the variable δ_t to denote the biological status

⁶Studies on the effect of family income on children's education mostly relied on realized income measures. There are only a few studies that have actually examined the relation between children's outcomes and income using parental income measures that overcome the endogeneity of parental income with respect to children's ability (Mayer, 1997; Blau, 1999; Plug, 1999; Shea, 2000).

⁷The measurement of cognitive ability or intelligence has a long history, and the prevailing idea is that IQ tests do a reasonable job in measuring it; see Spearman (1927) and more recently Cawley et al., (1996).

of the child: $\delta_t = 1$ if the child is adopted, and $\delta_t = 0$ if the child is a biological offspring. If e_{t-1}^* represents the parental abilities of biological parents of adopted children, the ability mobility relationship (2.2) is modified as follows:

$$e_t = b_0 + (b_1 - b_{g1}\delta_t)e_{t-1} + b_{1g}\delta_t e_{t-1}^* + v_t \quad (2.7)$$

Since the coefficient b_1 represents both genetic and cultural transfers, b_{g1} accounts for genetic transmission only. Note that we do not observe abilities of the natural parents of adopted children but that we do include $b_0^*\delta_t$ to correct for it. Inserting this into equation (2.6) yields a human capital function suitable for a sample of both biological and adopted children:

$$h_t = c_0 + b_0c_2 + b_0^*c_2\delta_t + c_1y_{t-1} + b_1c_2e_{t-1} - b_{g1}c_2\delta_t e_{t-1} + w_t + c_2v_t \quad (2.8)$$

Estimates of b_1c_2 and $b_{g1}c_2$ produce our nature and nurture estimates where a simple division disentangles environment from genes.

3 Estimation

In this model the children's human capital is measured as years of initial schooling. Schooling depends on observable attributes that vary within and across families, $x_{ik} = [z'_{ik}, z'_k]'$, and unobservable individual and family components η_{ik} , where i and k indexes individuals and families, respectively. Attributes that vary across members within a family are, for example, age of the child or gender. Examples of attributes that vary across families are family income, parental ability and education levels of parents. In our model we view heterogeneity due to unobserved family characteristics in the context of a random coefficient model. If the unobservable family components vary stochastically across families we write down

$$h_{ik} = \alpha' z_{ik} + \beta'_k z_k + \eta_{ik} \quad (3.1)$$

where

$$\beta_k = \beta + \eta_k \quad (3.2)$$

Substitution of (3.2) in (3.1) gives a linear schooling function

$$h_{ik} = \alpha' z_{ik} + \beta' z_k + \epsilon_{ik} \quad (3.3)$$

where $\epsilon_{ik} = \eta_{ik} + \eta'_k z_k$. The disturbance terms are normally distributed with means equal to 0 and variances denoted as $Var[\eta_{ik}] = \sigma_i^2$ and $Var[\eta_k] = \Gamma$. This implies that the distribution of ϵ_{ik} is normal; its mean is equal to

$$E[\epsilon_{ik}] = E[\eta_{ik} + \eta'_k z_k] = 0 \quad (3.4)$$

and variance is defined by

$$Var[\epsilon_{ik}] = E[\epsilon_{ik}\epsilon'_{ik}] = \sigma_i^2 + z'_k \Gamma z_k = \sigma_{ik}^2 \quad (3.5)$$

ϵ_{ik} is independent between households but correlates across members of the same household. The covariance between members i and j of family k is

$$Cov[\epsilon_{ik}, \epsilon_{jk}] = E[\epsilon_{ik}\epsilon'_{jk}] = z'_k \Gamma z_k \quad (3.6)$$

Hence, we will estimate is a linear schooling function that allows for familywise heteroscedasticity.

The distribution of ϵ_{ik} in (3.4)-(3.6) is indeed richly parameterized. This represents a drawback for the iterative maximization of the log-likelihood function defined below, as there is a distinct possibility that the iterated value of σ_k^2 (not to mention the final estimate) becomes negative for at least some k . This derails the maximization procedure. For this reason, we respecify the distributional assumption by allowing for familywise heteroscedasticity in the following manner:⁸

$$\sigma_{ik}^2 = \exp(\gamma_i) + \exp(\gamma' z_k) \quad (3.7)$$

The component of the variance that owes to the heterogeneity in unobserved family characteristics (η_k above) is given by $\exp(\gamma' z_k)$. Consequently the within-family correlation ρ_k between family members i and j may be defined as

$$\rho_k = \frac{\exp(\gamma' z_k)}{[\exp(\gamma_i) + \exp(\gamma' z_k)]^{1/2} [\exp(\gamma_j) + \exp(\gamma' z_k)]^{1/2}} \quad (3.8)$$

The use of exponentiation ensures positive values both for the variance σ_{ik}^2 and the correlation ρ_k .⁹

⁸The vector z_k does not include a constant. This constant would be only weakly identified, as γ_i already anchors the average variance.

⁹Individual characteristics (in our model, gender and being adopted) determine the variance but not the correlation coefficient because the latter is driven by family variables that are common across siblings. Overall, one might wish to simplify the model by omitting this complicated covariance structure. The estimation results strongly suggest that the heteroskedasticity and correlation characteristics of the covariance structure are empirically meaningful. Thus, a simpler model with an i.i.d. assumption would not yield consistent parameter estimates, owing to the frequent censoring on years of schooling.

We now turn to the derivation of the likelihood function. For reasons explained below, we consider a family with two children. Children who are still in school constitute censored observations and will be treated accordingly in our empirical analysis. Based on this information, we must make a distinction between three types of families: (i) those where all children have completed their school career; (ii) families where one of the children is still in school; and (iii) families where all children are still in school. For the first group the contribution to the likelihood function is

$$L_k^{(1)} = f(\epsilon_{ik}, \epsilon_{jk}) = \phi_2(\epsilon_{ik}/\sigma_{ik}, \epsilon_{jk}/\sigma_{jk}, \rho_k) / \sigma_{ik}\sigma_{jk} \quad (3.9)$$

where $\phi_2(\cdot, \cdot, \rho_k)$ is the standard bivariate normal probability density function (pdf) with correlation coefficient ρ_k . For families where one of the children has not completed school yet, we have a censored schooling variable resulting in a different schooling distribution. For a child still in school we know that his or her schooling career took at least h_{ik}^c years, and we know for certain the total period of schooling will be prolonged beyond h_{ik}^c . In this situation the likelihood function equals

$$L_k^{(2)} = \int_{s_{ik}}^{\infty} f(\epsilon_{ik}, \epsilon_{jk}) d\epsilon_{ik} = \phi_1(\epsilon_{jk})(1 - \Phi_1^c(s_{ik} | \epsilon_{jk})) / \sigma_{jk} \quad (3.10)$$

where ϕ_1 is the univariate standard normal pdf, and where

$$s_{ik} = h_{ik}^c - \alpha' z_{ik} - \beta' z_k \quad (3.11)$$

and where Φ_1^c is a conditional univariate standard normal cumulative distribution function (cdf), defined as

$$\Phi_1^c(s_{ik} | \epsilon_{jk}) = \Phi_1((s_{ik} + \rho_k \epsilon_{jk}) / \sigma_{ik} \sqrt{1 - \rho_k^2}) \quad (3.12)$$

and Φ_1 is the standard normal cdf. Finally, if all children are school going children the contribution to the likelihood function reads as

$$L_k^{(3)} = \int_{s_{ik}}^{\infty} \int_{s_{jk}}^{\infty} f(\epsilon_{ik}, \epsilon_{jk}) d\epsilon_{ik} d\epsilon_{jk} = \Phi_2(-s_{ik}/\sigma_{ik}, -s_{jk}/\sigma_{jk}, \rho_k) \quad (3.13)$$

where Φ_2 is the bivariate standard normal cdf with correlation ρ_k . Together, the equations (3.9), (3.10) and (3.13) summed over the respective household types form the likelihood function.

If a family has only one child or has more than two children, the likelihood function can be derived along similar lines. Conceptually, this is not difficult, but there are major practical obstacles. One is the censoring of

the dependent variable: for large families, censoring generates a multidimensional normal probabilities.¹⁰ To simplify the analysis, we restrict the sample to families with at least two siblings, and if a family has more than two children we randomly select two for the analysis. This greatly reduces the complexity of the programming effort and comes only at the cost of diminished precision and a small amount of randomness in the outcomes of the investigation.

An alternative approach to deal with unobserved family characteristics is to apply fixed effects estimators. By differencing schooling functions of siblings (or biological and adopted children) the unobservable components that vary across families drop out and observables that vary across siblings remain. The reason why we do not use fixed effects models is that we cannot estimate how much is attributed to environment and how much to genes. To disentangle nature from nurture we require both individual and family specific estimators where the family specific parameter measures the degree to which intelligent parents produce intelligent children and where the individual parameter removes genetical ability transfers for the adopted siblings.

4 Data

This paper employs the Wisconsin Longitudinal Survey which is an unique American dataset with information on people who were born around 1940. The collection of these data started in 1957 with a questionnaire administered to the complete cohort of students who graduated from a high school in the American state Wisconsin in that year. The information in that first wave relates to the children's social background (parents' education and occupation, numbers of older and younger sibling), intelligence (measured as standardized IQ test scores), and aspirations. Subsequently, research was continued on a randomly selected one third of the original cohort. In 1964 and 1975, the respondents was approached again to obtain information about, among others, their schooling and labor market careers. In 1992, the same sample of persons was contacted once more in order to collect new information about their labor market experiences between their late 30s and early 50's. As well, this latest round contained questions about many facets

¹⁰High-dimensional normal probabilities may be evaluated with simulation techniques; e.g., see Vijverberg (1997). However, with different households offering different dimensions, this is a daunting programming task, which we leave for future research.

of life events and attitudes. For more information on the WLS data, see, among others, Sewell and Hauser (1992) and Hauser et al. (1996).

Of particular interest for the present study, a set of questions targeted the educational attainment of the respondents' children. Respondents were asked to list for each child the highest grade or year of regular school that child ever attended, whether (s)he completed this grade or year, and whether (s)he attended a regular school in the last 12 months. From the information on educational attainment we create the variable "years of schooling." For those children who completed the highest level attended, years of schooling equals the number of years nominally required for that. Children who were still in school constitute censored observations and will be treated accordingly in our empirical analysis; this is the case for about 20 percent of our sample. Note that deleting these observations from the analysis will cause the results to be biased. This holds true especially for the age variable because in that case only low achieving young children will be included in the sample. As the respondents in the sample often have more than one child, we construct sibling information variables for each child. Finally, we use information on the relationship of the child to the respondent to distinguish adopted children from children with their biological parents.

The other explanatory variables are common to all children from one family. These variables can be divided into two groups: human capital variables and financial variables. We discuss each group in turn. Human capital variables are years of schooling of the children's parents (one of whom is a respondent of the original 1957 sample); the respondent's IQ score at age 16; and years of schooling of the respondent's parents. Financial variables included in our analysis are family income measured in 1992 and in 1975. Since income is positively correlated with the family's human capital variables, we need a human-capital-free income measure to separate the effect of income from the effects of human capital. Through a procedure outlined in detail in Section 5.1, we identify an income component that is not correlated with observed or even unobserved human capital: this component represents random income shocks.

The number of original observations we begin with in 1957 equals 10317, but we restrict ourselves basically to the 8500 people who responded to the 1992 questionnaire. In this paper we do not want to get involved in complications that arise if children are brought up in incomplete families. So, we select about 6700 standard families from which all childless and one-parent families are excluded. From the remaining families, about 1350 observations had to be removed from the analysis due to missing (or incomplete) obser-

vations on the family income measures in 1975 and 1992, on their children’s age, gender and educational attainment. At this point we have 5365 families and 13626 children in our sample. Then we restrict the sample to families with at least two children, and if a family has more than two children we randomly select two for the analysis. Finally, we exclude families where both children are adopted. We end up with a sample of 6460 children from 3230 families. Descriptive statistics appear in Table A1. The first column reports statistics on the restricted sample, the second column applies to all children in the WLS database.

5 Results

To gain insight into how human capital is transferred across different generations, the empirical results will be presented along the lines set out in Section 2. We begin with the analysis on human capital persistence across generations. In Table 1 we estimate equation (2.5). Among family-level variables we find, not surprisingly, that highly educated parents stimulate their children’s education, and that high scores on childhood IQ tests (of either mother or father) raises the number of years of schooling. The effect of both father’s and mother’s education is about the same. This seems at odds with what is usually observed (Becker, 1970; Haveman and Wolfe, 1995; Ermisch and Francesconi, 2000). They find that the level of education of the mother is more closely related to the educational attainment of the child than is that of the father.¹¹

Among individual-level determinants we find that younger children invest more in human capital than older ones, and that daughters stay in school somewhat longer. We also observe that having brothers or sisters has a negative effect on the educational attainment of children. Within families we find a positive correlation ρ_k (equation (3.8)) between educational achievement of siblings that is typically around 0.29, with minor variations across households.

¹¹Their argument is the following. Since women have inborn comparative advantages in home investment, and thus in raising children during their preschool years the impact of her education on their children’s school success is higher. We suspect that our findings are somewhat different because of sample selectivity with respect to parental education. We only examine families where one of the parents is at least a high school graduate. Since more education raises labor market attachment, mothers in our sample will probably spend relatively more time working and less time raising her offspring than the average U.S. (or Wisconsin) mother, which might explain our findings.

5.1 Does parental income matter?

It is clear from these results that there are large transfers of human capital between two generations. However, these estimates cannot tell whether parental human capital is transferred to the child through parental income, through genes, through social background variables, or through culture.

To address the question whether income has a positive impact on children's human capital accumulation, we estimate equation (2.6) using two different income measures; see Table 2. The first column utilizes family income measured in 1975. At this time the respondent is about 34 years old and, on average, his or her children will be in primary or the early years of secondary school. At this stage, schooling is compulsory, implying (at first glance) that family factors should at most have a muted effect. But recall that the dependent variable is completed (or, if so be the case, censored) years of schooling. 1975 family income may have two effects on eventually completed schooling. First, there is a lifecycle argument: schooling later on is paid for by savings from income received earlier. Second, early income is allocated to create a family environment that is conducive to the child's success in school, which in turn invites further schooling investment when the child has become a young adult. For both argument, it is mostly the permanent component in 1975 income that creates the effect. In any case, column 1 of Table 2 reports a strong positive parental income effect. In column 2, family income of 1992 is used. At this stage of the parental lifecycle, most children have just ended their schooling career, and college expenses may still be taking a big bite out of the parents' budget. Again, it is permanent income that matters. If parents anticipate on their future income (which is closely related to permanent income) while funding their children's education, 1992 income will still be important when the children have finished school. Even so, whether we use 1975 or 1992 income the estimated income effects are not substantially different. To see whether it is income in 1975 or income in 1992 that is most important we included both income measures simultaneously. Both estimates remain about the same. Parental income seems important, whether it is obtained when students are in their in early childhood, or when they already left school.

These robust findings indicate that permanent income matters, however, they do not necessarily tell us that parental income itself has a beneficial impact on children. The problem is that pure human capital and ability effects operate through income as well. A more sophisticated way to study parental income effects is to identify that part of parental income that repre-

sents luck. The idea is to imitate a lottery where money is given to randomly selected parents at different points in time, and then to track the subsequent school performance of their children. If income truly matters we should see at least two things. First, children should do better in school when parents are handed over their prize money when their offspring are still in school. And second, no effects are expected when parents win their lottery prize and children have already left school. Since parents cannot foresee (future) variation in their income when their children have finished school, it is impossible to anticipate on it while funding their children's education.

In this paper, it is this experiment we mimic. We extract random income shocks using information on 1975 and 1992 income. To be precise, we predict log family income in both 1975 and 1992 on the basis of observed human capital and ability measures, and we compute residuals for both years. The estimated equations from which residuals are computed are reported in the first part of Table 3. These new money measures will depend both on unobserved parental ability measures and luck in the market for the respective years. If one assumes that unobserved parental ability measures are correlated, and that luck components are not, regressing the 1992 income measure on the 1975 measure should pick up these unobserved parental abilities; the residual of this equation proxies that component of the 1992 family income that reasonably represents luck. And in reverse, if we regress the 1975 residual on our 1992 measure we obtain a measure for income generated by luck experienced in 1975. The equations from which the luck components are derived can be found in the second part of Table 3. Note that this technique purges any income determinant that remains constant over at least this portion of the lifecycle; this includes ethnic factors, personality traits, or indeed "structural luck."¹²

Now both luck components are entered into the children's human capital equation as a parental income measure; see Table 4. To estimate the true impact of parental income we compare the impact on the children's educational attainment of random income shocks experienced when children are still in school and when most children have left school. We observe that parental income effects fall in 1975 and 1992 but remain significantly different from zero.

By replacing family income with that income part that is generated by

¹²Notice that the "luck component" as derived here is closely related to the notion of transitory income. To be structurally lucky is similar to having a structurally positive flow of transitory income, which one would typically interpret as being a part of permanent income.

luck on the market, we end up with a hybrid model that contains elements of both (2.5) and (2.6). We avoid this problem if we add both luck components to the human capital transfer equation (2.5). This is what we do in column 2 and 3 of Table 1. Compared with column 1 of Table 1, the parental education and IQ effects remain almost identical. Both comparisons show however that lucky income measured in 1975 and 1992 exert their own effects.

These results are paradoxical in the light of the design of the lucky income variable and its timing. On the one hand, family income observed in 1975 matters even if one purges the income component that derives from ability transfers between parents and offspring. On the other hand, the analysis with 1992 income shows similar patterns. Should one conclude that the random income variable measures unobservable traits that drive educational achievement, such as personality? By design, such lifecycle traits have been purged away. Could it then be that the 1992 random income was not truly unforeseeable? One might argue that, because it is uncorrelated with 1975 income, it was not foreseeable in 1975 but that the 1992 random income variations are reflective of (un-)favorable financial events that played out over a longer period. In support of this, the effect of the 1975 random income seems larger (one third of the effect of total income, see Table 2) than a single year's variation ought to have on a lifecycle outcome such as a child's schooling. Thus, 1975 random incomes may well pertain to financial fortunes in years around 1975, not just 1975 itself. Such questions can only be answered with more frequent measurements of income.

However, if we repeat our experiment assuming that our observed random income shocks not only describe unanticipated shocks in years 1975 and 1992 itself, but also those received prior to both years, income matters if the 1975 random component affects all children where the 1992 component only hits those who are relatively young (and are still in school or left school recently). In Table 4 we estimate the previous model with 1975 and 1992 random income interacted with age. Compared to earlier results we find this time that it is only random income measured in 1992 that generates negative significant interacted age effects. Interacted 1975 random income effects are smaller and not significant. Apparently, income itself has to a certain extent a beneficiary influence on the child's school performance.

To summarize our income results, we tested the idea that a better access to financial resources improve the children's educational achievement in three different ways using (i) observed family income in 1975 and 1992; (ii) components of 1975 and 1992 family income that reasonably represent luck; and (iii) both luck components allowing for interactions with the child's age.

All tests demonstrate that permanent family income including permanent family factors like parental education, and parental IQ are decisive factors in explaining the relation between family income and the child's years spent in school. Only with the third method we are able to show that (transitory) family income itself matters too. This observation is in line with what previous researchers have found. That is, direct family income effects on the child's schooling attainment run foremost through the permanent component of family income. And if short run variation in family income (or transitory family income) exerts a positive influence its effect is rather limited (see Shea (2000), Cameron and Taber (2000), Chevalier and Lanot (1999), Cameron and Heckman (1998), Mayer (1997)).

5.2 Is it nature or nurture that matters?

So far we have been rather silent when it comes to the effects of ability. Fully in line with other literature, we find that parental IQ predicts school performance of children. This implies that the influence of IQ transcends over generations. An intriguing question deals with the problem of nature and nurture. Is it inheritance or is it the environment which is the primary factor in explaining schooling differences of children?

In this Section we will open the discussion on the heritability of IQ and use information on adopted children. We begin with estimating equation (2.6) adding an adoption dummy for adopted children to see how adopted children perform in school. In Table 5 we find that adopted children do worse with respect to the total years of schooling. We observe this for family income measured in 1975 and 1992.

To isolate that part of IQ that stems from genetic transmission we need to include the IQ covariate for adopted children. This is what we do in the second column of Table 5 where we estimate equation (2.8). IQ corrections for adopted children turn out to be negative which correspond with the idea that intelligence measured as childhood IQ is to a certain extent inherited. Note however that these effects are significantly negative in the margin. Only if we use family income measured in 1975 interacted IQ effects are significant at a 10 percent level. This turns out to be a cell size effect. In the present sample of 6460 children only 114 are adopted. Later on we will use a much larger sample and find all relevant adoption effects to be significantly different from zero.

Our model also provides estimates on how much can be attributed to environment and how much to genes. The parameter estimates attached to

the variable “IQ of parent” indicate the degree to which intelligent parents produce intelligent children who are more likely to obtain more schooling: these parameters combine cultural and biological effects, b_1c_2 . The parameters of the interaction effect “IQ of parent \times being adopted” (i.e., $b_{g1}c_2$) removes the direct genetical ability transfers that cannot occur with respect to adopted. From both parameters we conclude that both nature and nurture matter but also that genetics are the primary factor in explaining schooling differences of children. We find that of all ability transfers about 79 percent run through genes. Compared to Behrman and Taubman (1989) who estimate that about 80 percent of the variation in schooling can be attributed to the genes, we end up with almost identical numbers. Note that they arrive at their nature estimate using variance decomposition on a sample of relatives and twins while we decompose ability effects in the form of regression slopes on a sample of biological and adopted children.

In the third column we run the same regression using income representing luck as a regressor. The influence of IQ increases since it picks up that part of income that is generated by it. But the size of the genetic component ($b_{g1}c_2$) remains the same. Consequently, we find that of all ability transfers the genetic component falls from 79 to 65 percent.

5.3 Sons and daughters separately

So far we have pooled sons and daughters. However, it is possible that there is some human capital differentiation between girls and boys. Thus, the specifications reported above must be estimated separately for boys and girls (while at the same time allowing for common family heterogeneity factors). This is what we do in Table 6. Results are as follows.

The estimates in the first column show that parental IQ and 1975 income do not seem to affect sons and daughters differently. If we disentangle cultural from biological IQ effects we do observe differences. For sons we find that about 55 percent of parental IQ effects run through the genes. For daughters the genetic component amounts to 95 percent. Although the impact of nature is much higher for girls than it is for boys, differences are not significant. If we use our luck component of 1975 income we find that income effects fall and IQ effects rise. Our nature estimates show this time that with respect to IQ transfers and years spent in school about 42 and 90 percent are in his and her genes. By not treating 1975 income as an explicit environmental variable the nurture component of parental IQ compensates for the falling impact of parental income.

If we repeat the analysis with 1992 income, parental IQ effects remain similar, and income effects become somewhat higher for sons. Our nature estimates show that with respect to IQ transfers and educational outcomes 44 percent is in the genes for boys. Our 102 percent estimate for girls shows that it is all genetics. With 1992 income that is generated by market luck we find that the nature component for sons and daughters drop and become 32 and 90 percent respectively.

In the end, however, all likelihood ratio tests indicate that this model and the model we estimate in Table 6 are statistically identical (critical value is set at 14.1). Hence, in all four different specifications the estimates cannot reveal that boys and girls are affected differently by family background variables such as family income and parental IQ, or that the environment treats boys and girls differently.

6 Selectivity, adopting families and adopted children

While our nature and nurture estimates suggest that genes are rather decisive, we should treat our estimates with care. Since we do not observe ability of the natural parents of adopted children, the estimates may still suffer from ability bias. In fact, we are quite convinced that such a bias exists. To determine sources of this bias, it is instructive to return to our model once more. If e_{t-1}^* represents the parental abilities of biological parents of adopted children, the corrected ability mobility relation is defined as

$$e_t = b_0 + (b_1 - b_{g1}\delta_t)e_{t-1} + b_{g1}\delta_t e_{t-1}^* + v_t \quad (6.1)$$

which implies that the human capital function reads as

$$h_t = c_0 + b_0c_2 + c_1y_{t-1} + b_1c_2e_{t-1} - b_{g1}c_2\delta_te_{t-1} + b_{g1}c_2\delta_te_{t-1}^* + w_t + c_2v_t \quad (6.2)$$

With this in mind, we briefly outline some of the potential dangers of ability bias.

- **Selection in genes and adopted children.**

Children who are given up for adoption are more likely to have less favorable socio-economic backgrounds. The mechanism to explain why

adopted children are on average less intelligent is built on the positive relation between ability and income. Young single mothers, or poor families in developing countries, face on average more difficulties to make ends meet, and are therefore more likely to register their children for adoption. These children will be on average less endowed. If this negative correlation between being adopted, δ_t , and ability of natural parent(s), e_{t-1}^* , is picked up by the estimated adoption parameter, our nature estimate overestimates the impact of genetic transfers.

- **Selection in environment and adopted children.**

In our model we isolate environmental influences in which children are brought up. For adopted children, however, the influence of the environment may differ because there is heterogeneity with respect to the age these children met their adopting families. We end up only estimating an average correction for being adopted. If we assume the environmental contribution to ability is maximal for children who are adopted as babies, the implication is that for children in our sample the genetic influence is biased upwards.

If cultural transfers within a family are assumed equal for children who are adopted as babies and children who are brought up by their biological parents, the argument goes as follows. With b_{c1} as the cultural transfer parameter, the ability mobility relation reads as

$$e_t = b_0 + (b_{c1} + b_{g1})(1 - \delta_t)e_{t-1} + b_{c1}\delta_t e_{t-1} + b_{g1}\delta_t e_{t-1}^* + v_t$$

With the information at hand we are only able to measure an average environmental correction for adopted children

$$e_t = b_0 + (b_{c1} + b_{g1})(1 - \delta_t)e_{t-1} + b_{c1}^*\delta_t e_{t-1} + b_{g1}\delta_t e_{t-1}^* + v_t$$

where b_{c1}^* represents this average effect. The modified ability relation is written down as

$$e_t = b_0 + b_1 e_{t-1} - b_{g1}\delta_t e_{t-1} + (b_{c1}^* - b_{c1})\delta_t e_{t-1} + b_{g1}\delta_t e_{t-1}^* + v_t$$

Compared to equation (6.1) we end up with an additional part $(b_{c1}^* - b_{c1})\delta_t e_{t-1}$. With adopted babies in mind this term is negative implying that the genetic effect we estimate is biased upwards. For children

who were just brought to their adoption families, the estimated nature correction is of course too low.

Note that in this situation selection effects occur not because we do not observe the ability of the natural parents but because we fail to observe when these children are placed in adoption families.

- **Selection and adopting families.**

In many situations adoption agencies have specific family recruitment programs to sort out families who are suitable for adoption. Hence, adoption families are likely to have more favorable socio-economic backgrounds. For our estimates this has no consequences because we observe their ability, e_{t-1} and therefore correct for this potential bias.

- **Selection and matching mechanisms.**

So far, we assumed that adoption families and their adopted children were randomly matched. Problems occur if there is endogeneity in the matching process. For example, adoption agencies may have matching strategies where information on the natural mother's education, working career et cetera is used to match the children of natural mothers to adopting families. Also families may choose their adoption children on the basis of similarities.

If we speak of perfect assortative matching the families ability component e_{t-1} would be "identical" to e_{t-1}^* implying that observed nature effects would fully disappear. Any observable adoption effects would then be attributed to differences in raising these children. More specifically, adoption effects would exist only if (i) parents emotionally and materially differentiate between biological and adopted children, or (ii) adopted children fail to receive the life-long nurture effects because, by definition, they are placed in adoption families at a later age.

If we assume an imperfect assortative matching mechanism fortunate families will have on average adopted children with a higher ability. And biased estimates are produced to the extent that e_{t-1} and e_{t-1}^* are positively correlated. The result is that nature effects will be underestimated.

- **Differentials in upbringing.**

The interpretation of our nature estimate requires that parents do not differentiate between their biological and adopted children. That is,

families should treat their children equally with respect to the time and money they invest in them. This does not imply that our model cannot account for potential behavioral differences. In fact, treatment differentials are partly accounted for adoption dummies in (2.8).¹³ However, if these differences in upbringing end up in our observed b_{g1} estimate, interpretation of our heritability factor becomes troublesome.

To see how our nature estimate is affected we discuss three motives why parents treat adopted children differently from their biological ones. The first motive assumes that parents care equally about their children's welfare. In this situation parents choose to invest more in their adopted children to compensate for their ability deficit. The second motive is less altruistic. Parents only invest to generate the highest return. In this situation adopted children receive less educational funding. The third motive is mostly selfish. Parents may be expecting closer ties (financial and otherwise) in their old age with their biological children than with their adopted ones. Thus, they invest more in the education of their biological children.

Implications for our nature estimate are the following. If parents invest less in their adopted children nature effects will be overestimated. And if parents invest more in their adopted children the effects are reversed.

To test how serious some of these selection effects really are, we would need to know the socio-economic background of the biological parents of adopted children, and information on the timing of the adoption. The WLS does not provide this information. Hence, testing is not possible.

We begin to shed light on the things we do know. Table 7 tabulates means and standard deviations of biological and adopted children. The variables can be divided into two distinctive groups: individual variables, and social background variables. We discuss each group in turn.

With respect to individual variables we start with comparing the years of education across adopted and biological children for different genders. Conform the results in Table 5 we find that non-adopted children accumulate more human capital than adopted children. Adopted children are typically 2.4 years younger, and, as a consequence, are more likely to be in school still. Since the WLS is a cohort survey, this also implies that adopting parents

¹³In addition to the observed differences between biological and adopted children, we allow for differences in the unobservables too. That is, we vary the variance σ_k^2 to the extent that random variation in both ability and schooling variables come from different distributions for adopted and biological children.

are usually older than biological parents. Simple t-statistics indicate that with the exception of gender all the differences are significant; see column 3, Table 7.

With respect to family background variables we find significant differences too. Adopting families have on average fewer children. The structural differences in the socioeconomic characteristics of biologically related and adopting families indicate that either adopting agencies or adopting families are selective. Adopting families turn out to be above average in all their socioeconomic characteristics. Note furthermore that although observed differences in individual and family characteristics are favorable for the human capital accumulation of adopted children the estimates in Table 5 show that adopted children remain worse off with respect to years of schooling even when we control for their favorable individual and background characteristics.

So far, two things have become clear. First, adopted and biological children structurally differ in their observables. Second, if adopted and biological children structurally differ in their unobservables the nature and nurture estimates suffer from ability bias. In most situations the bias points to overestimated nature effects. In fact, we can only think of two clear selectivity effects where our heritability estimate is too low: (i) if adoption agencies use corresponding qualities of both natural and adoptive parents as a matching strategy, and (ii) if parents invest more time and money in adopted children. In the remainder of this Section, we will argue (and test) that these two situations are not fully applicable, and that our nurture estimate of 20 to 35 percent turns out to be a rather conservative estimate.

Do adoption agencies use matching strategies based on similarities between adopted child and adoptive parents, and select therefore families with relatively less favorable socio-economic backgrounds? In Table 8 we test whether adoption families are randomly drawn from the population at large. We find that adoption agencies are not blind. Estimates of simple logit models indicate that the chances of a household being adoptive rise especially when the mother is more educated. Parental IQ does not matter. For our exercise this result is fortunate, but not unexpected. Agencies do not have information on the IQ levels of adopting parents. Note that we are aware that these logits are reduced form models and can also be interpreted as if adoption families select themselves—but if so, one would have expected a more prominent role of IQ. Since it is not clear whether agencies use the described matching procedures, and since IQ effects are fairly small the resulting bias is probably not substantial.

Do parents treat their adopted children differently? We are inclined to say no since we have analyzed only families with both biological and adopted children. If a different upbringing within a family leads to stigmatization, and parents realize that this is damaging for their children's career they will act accordingly. Still some previous researchers have found that parents may feel the urge to protect their own genetic material and as a consequence invest less in their adopted children (Dawkins, 1976; Case, Fin and McLanahan, 2000). If the latter is the case our nature estimate is too high.

As a final test of robustness, we estimate the earlier models in Table 5 using an alternative sample and a simplified estimation procedure. This sample now contains all children in the WLS database. The simplified estimation procedure allows for censored observations, assumes independence between family members, and does not allow for unobserved heterogeneity. Results are tabulated in Table 9. The parameter estimates do not differ much compared to those presented in Table 5, with one exception, namely that this time all relevant adoption parameters significantly differ from zero.¹⁴ With respect to the genetic component in the ability transfers we find the same high proportions.

In summary, we expect our nature and nurture estimates to be biased. Our results do provide some useful insights. We find that, of the total ability transfer, the statistics of 65 to 79 percent may be viewed as upper bounds of our nature estimates. The observation that nature is more dominant in explaining schooling differences remains.

7 Concluding remarks

Intergenerational mobility literature shows persistently that children raised in high educated families are higher educated than children raised in low educated families. In this paper we examine whether ability measured as IQ is the dominant factor behind this family connection. In it, we find that parental IQ matters for the educational attainment of children. Nevertheless, the notion that high ability parents produce high ability children who are more likely to obtain more schooling is not the only mechanism at work. Our sample reveals two additional mechanisms: (i) if we control for parental ability in the children's schooling function parental education is found to be

¹⁴In the sample used for Table 5, 114 children were adopted. Here, 545 children are adopted, which accounts for the relatively greater increase in precision of the adoption parameters.

of importance too; and (ii) if we trace back those students whose parents experienced “lucky” (or random) income shocks we find that parental income exerts a positive influence on the educational attainment of the children.

We further exploit a special feature of the dataset and disentangle persistence effects caused by nature and nurture. Using information whether these children are their parents’ own offspring as opposed to adopted children, we find that about 65 to 79 percent of the ability effects relevant for school achievement can be attributed to genetic effects. We explore reasons why these nature estimates may be biased, and we conclude that they are likely biased upwards.

Our results thus indicate that it is rather complicated to find out which factors are exactly behind this family connection. From our exercise we learn at least four things: (i) that it is only to a certain extent that a better access to financial resources is an important factor in explaining the educational attainment of children; (ii) that ability and a more favorable academic environment do explain variation in the children’s years of schooling; (iii) that the largest part of ability relevant for education is inherited; and (iv) that, in these regards, there is no difference between sons and daughters.

As a final note, the public policy implications of these findings are rather significant. Much money is spent on the educational system. The underlying rationale is to create an environment in which students flourish. If nurture drives the success of children in school, a one-time equalization of educational opportunities will erase past inequalities in schooling; the next generation of children will start out equally. On the other hand, if children’s ability is determined to a large extent genetically, a nurturing school environment may help the less able children to overcome their disadvantage only at great cost; moreover, the ability of the next generation of children is still unequally distributed. In the former case, the rationale behind educational expenses is primarily productive and only once redistributive; in the latter case, educational expenses are repeatedly redistributive and only secondarily productive. This tension defines the political debate on educational financing and explains the boom-and-bust nature of educational budgeting.

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Appendix A

Descriptive statistics are reported in Table A1.

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Table A1: Descriptive statistics, means and standard deviations

WLS samples:	restricted		full	
first child			all children	
years of education	13.328	<i>2.541</i>	years of education	13.238 <i>2.597</i>
still in school (censored)	0.234	<i>0.423</i>	still in school (censored)	0.229 <i>0.420</i>
gender (daughter)	0.478	<i>0.499</i>	gender (daughter)	0.488 <i>0.499</i>
age	26.283	<i>5.043</i>	age	26.231 <i>5.171</i>
being adopted	0.017	<i>0.132</i>	being adopted	0.040 <i>0.196</i>
second child			number of	
years of education	13.347	<i>2.546</i>	children	13626
still in school (censored)	0.208	<i>0.406</i>		
gender (daughter)	0.486	<i>0.499</i>		
age	26.514	<i>5.079</i>		
being adopted	0.017	<i>0.130</i>		
family			family	
number of siblings	2.323	<i>1.339</i>	number of siblings	2.243 <i>1.511</i>
IQ parent	10.064	<i>1.406</i>	IQ parent	10.161 <i>1.418</i>
education of father in years	13.422	<i>2.541</i>	education of father in years	13.627 <i>2.666</i>
education of mother in years	12.810	<i>1.697</i>	education of mother in years	12.915 <i>1.763</i>
log family income 1975	9.678	<i>0.486</i>	log family income 1975	9.698 <i>0.491</i>
log family income 1992	10.966	<i>0.655</i>	log family income 1992	11.000 <i>0.656</i>
log random income 1975	0.000	<i>0.428</i>	log random income 1975	0.000 <i>0.435</i>
log random income 1992	0.000	<i>0.552</i>	log random income 1992	0.000 <i>0.555</i>
number of			number of	
children and families	3230		families	5365

Standard deviations in italics

Table 1: Education and parental human capital effects

years of education						
intercept	8.272	<i>0.386***</i>	8.305	<i>0.386***</i>	8.309	<i>0.385***</i>
daughter	0.126	<i>0.054***</i>	0.127	<i>0.054***</i>	0.131	<i>0.054***</i>
age	-0.072	<i>0.007***</i>	-0.074	<i>0.007***</i>	-0.073	<i>0.007***</i>
IQ of parent	0.151	<i>0.023***</i>	0.152	<i>0.023***</i>	0.153	<i>0.023***</i>
education father	0.252	<i>0.015***</i>	0.252	<i>0.015***</i>	0.250	<i>0.015***</i>
education mother	0.254	<i>0.022***</i>	0.253	<i>0.022***</i>	0.252	<i>0.022***</i>
random income 1975			0.261	<i>0.073***</i>		
random income 1992					0.321	<i>0.053***</i>
number of siblings	-0.124	<i>0.021***</i>	-0.119	<i>0.021***</i>	-0.126	<i>0.021***</i>
variance of years of education						
intercept	1.194	<i>0.023***</i>	1.196	<i>0.023***</i>	1.195	<i>0.024***</i>
daughter	-0.194	<i>0.030***</i>	-0.194	<i>0.030***</i>	-0.203	<i>0.031***</i>
IQ of parent	-0.063	<i>0.032**</i>	-0.064	<i>0.032**</i>	-0.051	<i>0.032*</i>
education father	0.070	<i>0.020***</i>	0.071	<i>0.023***</i>	0.061	<i>0.021***</i>
education mother	0.009	<i>0.027</i>	0.006	<i>0.029</i>	0.009	<i>0.028</i>
random income 1975			-0.021	<i>0.133</i>		
random income 1992					-0.049	<i>0.073</i>
number of siblings	-0.113	<i>0.036***</i>	-0.109	<i>0.037***</i>	-0.120	<i>0.037***</i>
Mean loglikelihood	-3.444		-3.441		-3.438	
N	3230		3230		3230	

Standard errors in italics; * significant at 10% level, ** significant at 5% level, et cetera

Table 2: Education and parental income effects

years of education						
intercept	5.975	<i>0.655***</i>	5.744	<i>0.570***</i>	2.668	<i>0.745***</i>
daughter	0.157	<i>0.056***</i>	0.162	<i>0.055***</i>	0.161	<i>0.055***</i>
age	-0.110	<i>0.007***</i>	-0.103	<i>0.007***</i>	-0.104	<i>0.007***</i>
IQ of parent	0.359	<i>0.023***</i>	0.315	<i>0.023***</i>	0.299	<i>0.023***</i>
log income 1975	0.824	<i>0.065***</i>			0.502	<i>0.072***</i>
log income 1992			0.771	<i>0.047***</i>	0.623	<i>0.052***</i>
number of siblings	-0.173	<i>0.022***</i>	-0.178	<i>0.021***</i>	-0.167	<i>0.022***</i>
variance of years of education						
individual component						
intercept	1.217	<i>0.025***</i>	1.211	<i>0.025***</i>	1.211	<i>0.024***</i>
daughter	-0.182	<i>0.033***</i>	-0.206	<i>0.034***</i>	-0.204	<i>0.033***</i>
family component						
IQ of parent	0.120	<i>0.040***</i>	0.145	<i>0.040***</i>	0.128	<i>0.043***</i>
log income 1975	-0.057	<i>0.046</i>			-0.038	<i>0.071</i>
log income 1992			-0.071	<i>0.039**</i>	-0.024	<i>0.060</i>
number of siblings	-0.095	<i>0.040***</i>	-0.110	<i>0.038***</i>	-0.111	<i>0.040***</i>
Mean loglikelihood	-3.520		-3.507		-3.500	
N	3230		3230		3230	

Standard errors in italics; * significant at 10% level, ** significant at 5% level, et cetera

Table 3: Estimating the luck components of family income in 1975 and 1992

Part I: Estimating family income using observed human capital characteristics

log family income:	1975		1992	
intercept	8.466	<i>0.074***</i>	8.825	<i>0.095***</i>
female	-0.045	<i>0.016***</i>	-0.142	<i>0.020***</i>
IQ parent	0.025	<i>0.006***</i>	0.064	<i>0.008***</i>
education of father	0.041	<i>0.004***</i>	0.061	<i>0.005***</i>
education of mother	0.023	<i>0.005***</i>	0.044	<i>0.007***</i>
education of grandfather	0.008	<i>0.003***</i>	0.007	<i>0.004*</i>
education of grandmother	0.002	<i>0.003</i>	0.007	<i>0.004*</i>
R-square	0.120		0.197	
N	3230		3230	

Part II: Estimating random income using unobserved human capital characteristics

log unexplained income:	1975		1992	
intercept	0.000	<i>0.007</i>	0.000	<i>0.009</i>
unexplained income 1975			0.438	<i>0.021***</i>
unexplained income 1992	0.264	<i>0.012***</i>		
R-square	0.115		0.115	
N	3230		3230	

Standard errors in italics; * significant at 10% level, ** significant at 5% level, et cetera

Table 4: Education and random parental income effects

years of education				
intercept	13.619	<i>0.316***</i>	13.599	<i>0.315***</i>
daughter	0.156	<i>0.056***</i>	0.159	<i>0.056***</i>
age	-0.112	<i>0.008***</i>	-0.111	<i>0.007***</i>
IQ of parent	0.405	<i>0.023***</i>	0.405	<i>0.023***</i>
random income 1975	0.280	<i>0.073***</i>		
random income 1992			0.369	<i>0.058***</i>
number of siblings	-0.199	<i>0.022***</i>	-0.205	<i>0.022***</i>
variance of years of education				
individual component				
intercept	1.218	<i>0.025***</i>	1.214	<i>0.025***</i>
daughter	-0.176	<i>0.034***</i>	-0.183	<i>0.035***</i>
family component				
IQ of parent	0.079	<i>0.009***</i>	0.080	<i>0.009***</i>
random income 1975	0.048	<i>0.107</i>		
random income 1992			0.033	<i>0.064</i>
number of siblings	-0.116	<i>0.037***</i>	-0.120	<i>0.037***</i>
Mean loglikelihood	-3.542		-3.538	
N	3230		3230	
<hr/>				
years of education				
intercept	13.627	<i>0.316***</i>	13.603	<i>0.315***</i>
daughter	0.157	<i>0.057***</i>	0.156	<i>0.056***</i>
age	-0.112	<i>0.008***</i>	-0.111	<i>0.007***</i>
IQ of parent	0.405	<i>0.023***</i>	0.406	<i>0.023***</i>
random income 1975	0.639	<i>0.540</i>		
random income 1975×age	-0.012	<i>0.019</i>		
random income 1992			1.025	<i>0.393***</i>
random income 1992×age			-0.023	<i>0.014**</i>
number of siblings	-0.200	<i>0.022***</i>	-0.205	<i>0.022***</i>
variance of years of education				
individual component				
intercept	1.219	<i>0.025***</i>	1.213	<i>0.025***</i>
daughter	-0.176	<i>0.034***</i>	-0.182	<i>0.035***</i>
family component				
IQ of parent	0.079	<i>0.009***</i>	0.080	<i>0.009***</i>
random income 1975	0.059	<i>0.110</i>		
random income 1992			0.037	<i>0.065</i>
number of siblings	-0.117	<i>0.038***</i>	-0.119	<i>0.037***</i>
Mean loglikelihood	-3.542		-3.537	
N	3230		3230	

Standard errors in italics; * significant at 10% level, ** significant at 5% level, et cetera

Table 5: Education and nature and nurture effects of parental ability

years of education						
intercept	5.978	<i>0.651***</i>	5.937	<i>0.652***</i>	13.614	<i>0.317***</i>
daughter	0.154	<i>0.056***</i>	0.154	<i>0.056***</i>	0.154	<i>0.057***</i>
age	-0.112	<i>0.007***</i>	-0.112	<i>0.007***</i>	-0.114	<i>0.008***</i>
IQ of parent	0.361	<i>0.023***</i>	0.365	<i>0.023***</i>	0.412	<i>0.023***</i>
log income 1975	0.828	<i>0.064***</i>	0.829	<i>0.064***</i>		
log random income 1975					0.281	<i>0.073***</i>
number of siblings	-0.176	<i>0.022***</i>	-0.175	<i>0.022***</i>	-0.201	<i>0.022***</i>
being adopted	-0.713	<i>0.315**</i>	2.259	<i>2.330</i>	2.259	<i>2.280</i>
being adopted×IQ of parent			-0.289	<i>0.226*</i>	-0.285	<i>0.223*</i>
variance of years of education						
individual component						
intercept	1.206	<i>0.025***</i>	1.205	<i>0.025***</i>	1.207	<i>0.025***</i>
daughter	-0.173	<i>0.033***</i>	-0.172	<i>0.033***</i>	-0.168	<i>0.035***</i>
being adopted	0.432	<i>0.109***</i>	0.380	<i>0.108***</i>	0.386	<i>0.116***</i>
family component						
IQ of parent	0.115	<i>0.040***</i>	0.116	<i>0.040***</i>	0.079	<i>0.009***</i>
log income 1975	-0.053	<i>0.046</i>	-0.053	<i>0.046</i>		
log random income 1975					0.044	<i>0.109</i>
number of siblings	-0.099	<i>0.040***</i>	-0.099	<i>0.040***</i>	-0.119	<i>0.037***</i>
Mean loglikelihood	-3.517		-3.517		-3.539	
N	3230		3230		3230	
genetic component in ability (b_{g1}/b_1)						
nature effects			0.791		0.691	
years of education						
intercept	5.771	<i>0.569***</i>	5.743	<i>0.569***</i>	13.595	<i>0.316***</i>
daughter	0.159	<i>0.056***</i>	0.160	<i>0.056***</i>	0.157	<i>0.057***</i>
age	-0.104	<i>0.007***</i>	-0.104	<i>0.007***</i>	-0.112	<i>0.007***</i>
IQ of parent	0.317	<i>0.023***</i>	0.320	<i>0.023***</i>	0.412	<i>0.023***</i>
log income 1992	0.773	<i>0.047***</i>	0.773	<i>0.047***</i>		
log random income 1992					0.369	<i>0.057***</i>
number of siblings	-0.182	<i>0.021***</i>	-0.181	<i>0.021***</i>	-0.207	<i>0.022***</i>
being adopted	-0.744	<i>0.302***</i>	1.836	<i>2.227</i>	2.055	<i>2.265</i>
being adopted×IQ of parent			-0.251	<i>0.216</i>	-0.266	<i>0.221</i>
variance of years of education						
individual component						
intercept	1.201	<i>0.025***</i>	1.200	<i>0.025***</i>	1.202	<i>0.025***</i>
daughter	-0.199	<i>0.034***</i>	-0.198	<i>0.034***</i>	-0.175	<i>0.036***</i>
being adopted	0.377	<i>0.117***</i>	0.334	<i>0.116***</i>	0.380	<i>0.119***</i>
family component						
IQ of parent	0.139	<i>0.040***</i>	0.139	<i>0.040***</i>	0.080	<i>0.009***</i>
log income 1992	-0.065	<i>0.039*</i>	-0.065	<i>0.039*</i>		
log random income 1992					0.059	<i>0.066</i>
number of siblings	-0.115	<i>0.038***</i>	-0.115	<i>0.038***</i>	-0.122	<i>0.037***</i>
Mean loglikelihood	-3.505		-3.504		-3.535	
N	3230		3230		3230	
genetic component in ability (b_{g1}/b_1)						
nature effects			0.784		0.645	

Standard errors in italics; * significant at 10% level, ** significant at 5% level, et cetera

Table 6: Education, nature and nurture effects for sons and daughters

years of education of boys				
intercept	6.154	<i>0.927***</i>	13.827	<i>0.432***</i>
age	-0.117	<i>0.010***</i>	-0.119	<i>0.010***</i>
IQ of parent	0.368	<i>0.032***</i>	0.416	<i>0.032***</i>
log income 1975	0.828	<i>0.091***</i>		
log random income 1975			0.270	<i>0.099***</i>
number of siblings	-0.151	<i>0.030***</i>	-0.178	<i>0.030***</i>
being adopted	1.513	<i>2.239</i>	1.209	<i>2.359</i>
being adopted×IQ of parent	-0.202	<i>0.218</i>	-0.177	<i>0.231</i>
years of education of girls				
intercept	5.746	<i>0.890***</i>	13.495	<i>0.444***</i>
age	-0.104	<i>0.011***</i>	-0.106	<i>0.011***</i>
IQ of parent	0.363	<i>0.032***</i>	0.410	<i>0.032***</i>
log income 1975	0.836	<i>0.087***</i>		
log random income 1975			0.297	<i>0.098***</i>
number of siblings	-0.202	<i>0.032***</i>	-0.227	<i>0.032***</i>
being adopted	2.760	<i>4.203</i>	3.117	<i>4.006</i>
being adopted×IQ of parent	-0.347	<i>0.407</i>	-0.371	<i>0.390</i>
variance of years of education				
boy component				
intercept	1.043	<i>0.029***</i>	1.048	<i>0.030***</i>
being adopted	-0.237	<i>0.498</i>	-0.153	<i>0.492</i>
girl component				
intercept	1.196	<i>0.025***</i>	1.198	<i>0.025***</i>
being adopted	0.692	<i>0.144***</i>	0.684	<i>0.150***</i>
family component				
IQ of parent	0.118	<i>0.041***</i>	0.079	<i>0.009***</i>
log income 1975	-0.056	<i>0.046</i>		
log random income 1975			0.026	<i>0.111</i>
number of siblings	-0.099	<i>0.041***</i>	-0.120	<i>0.038***</i>
Mean loglikelihood	-3.516		-3.538	
N	3230		3230	
genetic component in ability (b_{g1}/b_1)				
nature effect sons	0.548		0.425	
nature effect daughters	0.955		0.904	
likelihood ratio tests	7.429		6.201	

Standard errors in italics; * significant at 10% level, ** significant at 5% level, et cetera

Table 6 continued: Education, nature and nurture effects for sons and daughters

years of education of boys				
intercept	4.788	<i>0.777***</i>	13.772	<i>0.427***</i>
age	-0.105	<i>0.010***</i>	-0.116	<i>0.010***</i>
IQ of parent	0.309	<i>0.032***</i>	0.415	<i>0.032***</i>
log income 1992	0.880	<i>0.065***</i>		
log random income 1992			0.454	<i>0.077***</i>
number of siblings	-0.155	<i>0.029***</i>	-0.186	<i>0.030***</i>
being adopted	0.810	<i>2.205</i>	0.784	<i>2.343</i>
being adopted×IQ of parent	-0.137	<i>0.214</i>	-0.135	<i>0.229</i>
years of education of girls				
intercept	6.696	<i>0.784***</i>	13.487	<i>0.444***</i>
age	-0.101	<i>0.011***</i>	-0.106	<i>0.011***</i>
IQ of parent	0.330	<i>0.032***</i>	0.410	<i>0.032***</i>
log income 1992	0.673	<i>0.066***</i>		
log random income 1992			0.295	<i>0.077***</i>
number of siblings	-0.210	<i>0.031***</i>	-0.232	<i>0.031***</i>
being adopted	2.644	<i>3.970</i>	3.141	<i>3.946</i>
being adopted×IQ of parent	-0.337	<i>0.385</i>	-0.373	<i>0.384</i>
variance of years of education				
boy component				
intercept	1.006	<i>0.029***</i>	1.035	<i>0.030***</i>
being adopted	-0.215	<i>0.449</i>	-0.150	<i>0.447</i>
girl component				
intercept	1.190	<i>0.025***</i>	1.193	<i>0.026***</i>
being adopted	0.614	<i>0.151***</i>	0.672	<i>0.153***</i>
family component				
IQ of parent	0.136	<i>0.041***</i>	0.080	<i>0.009***</i>
log income 1992	-0.062	<i>0.041*</i>		
log random income 1992			0.087	<i>0.073</i>
number of siblings	-0.116	<i>0.039***</i>	-0.124	<i>0.038***</i>
Mean loglikelihood	-3.503		-3.534	
N	3230		3230	
genetic component in ability (b_{g1}/b_1)				
nature effect sons	0.443		0.325	
nature effect daughters	1.021		0.909	
likelihood ratio tests	11.175		8.075	

Standard errors in italics; * significant at 10% level, ** significant at 5% level, et cetera

Table 7: Descriptive statistics of biological and adopted children

	biological		adopted		<i>t</i> test
	mean	sd	mean	sd	
individual characteristics					
years of education	13.352	<i>2.516</i>	12.412	<i>3.036</i>	3.888
still in school (censored)	0.228	<i>0.419</i>	0.368	<i>0.484</i>	-3.483
gender (daughters)	0.478	<i>0.499</i>	0.464	<i>0.500</i>	0.278
age	26.376	<i>5.005</i>	23.790	<i>5.540</i>	5.395
family characteristics					
number of siblings	2.341	<i>1.346</i>	1.815	<i>0.991</i>	4.129
IQ parent	10.049	<i>1.401</i>	10.467	<i>1.487</i>	-3.118
years of education father	13.387	<i>2.525</i>	14.377	<i>2.810</i>	-4.094
years of education mother	12.782	<i>1.670</i>	13.562	<i>2.177</i>	-4.834
log family income 1975	9.674	<i>0.486</i>	9.803	<i>0.446</i>	-2.795
log family income 1992	10.960	<i>0.655</i>	11.140	<i>0.642</i>	-2.895
number of observations	3116		114		

Table 8: Adoption families and selection effects: estimates of a logit model

simple model						
intercept	-5.025	<i>0.631***</i>	-5.663	<i>0.583***</i>	-5.446	<i>1.714***</i>
IQ of parent	0.195	<i>0.060***</i>				
education father			0.083	<i>0.036**</i>		
education mother			0.113	<i>0.052**</i>		
log income 1975					0.249	<i>0.175</i>
Pseudo R-square	0.008		0.018		0.001	
full model						
intercept	-5.799	<i>1.697</i>	-5.825	<i>1.430***</i>		
IQ of parent	0.093	<i>0.066</i>	0.095	<i>0.067</i>		
education father	0.070	<i>0.039*</i>	0.071	<i>0.039*</i>		
education mother	0.102	<i>0.053*</i>	0.103	<i>0.053*</i>		
log income 1975	-0.051	<i>0.181</i>				
log income 1992			-0.046	<i>0.139</i>		
Pseudo R-square	0.019		0.020			
<i>N</i>	3230		3230		3230	

Standard errors in italics; * significant at 10% level, ** significant at 5% level, et cetera

Table 9: Education and nature and nurture effects using all children in the full WLS sample

years of education				
intercept	6.735	<i>0.433***</i>	13.873	<i>0.218***</i>
daughter	0.173	<i>0.040***</i>	0.171	<i>0.040***</i>
age	-0.113	<i>0.005***</i>	-0.116	<i>0.005***</i>
IQ of parent	0.326	<i>0.014***</i>	0.372	<i>0.014***</i>
log income 1975	0.772	<i>0.041***</i>		
log random income 1975			0.301	<i>0.045***</i>
number of siblings	-0.161	<i>0.012***</i>	-0.179	<i>0.012***</i>
being adopted	1.768	<i>0.745***</i>	1.736	<i>0.755***</i>
being adopted×IQ of parent	-0.246	<i>0.071***</i>	-0.239	<i>0.071***</i>
Mean loglikelihood	-1.774		-1.785	
N	13626		13626	
genetic component in ability (b_{g1}/b_1)				
nature effects	0.754		0.642	
years of education				
intercept	6.561	<i>0.380***</i>	13.886	<i>0.217***</i>
daughter	0.174	<i>0.039***</i>	0.172	<i>0.040***</i>
age	-0.107	<i>0.005***</i>	-0.115	<i>0.005***</i>
IQ of parent	0.286	<i>0.015***</i>	0.370	<i>0.014***</i>
log income 1992	0.722	<i>0.031***</i>		
log random income 1992			0.318	<i>0.036***</i>
number of siblings	-0.163	<i>0.012***</i>	-0.184	<i>0.012***</i>
being adopted	1.539	<i>0.740***</i>	1.599	<i>0.754***</i>
IQ of parent×being adopted	-0.225	<i>0.070***</i>	-0.226	<i>0.071***</i>
Mean loglikelihood	-1.767		-1.783	
N	13626		13626	
genetic component in ability (b_{g1}/b_1)				
nature effects	0.786		0.611	

Standard errors in italics; * significant at 10% level, ** significant at 5% level, et cetera