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ABSTRACT
Schooling, Family Background, and Adoption: Is it Nature or is it Nurture?[*]

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 at most 65 percent of the parental ability is genetically transmitted.

JEL Classification: I21, J13, J24

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1 Introduction

Many studies show that children raised by highly educated parents receive more schooling than children raised by less educated parents. The economics literature examines this family connection with models where parental resources are linked to the educational attainment of children through human capital investments (Becker and Tomes, 1986; Haveman and Wolfe, 1995). With the empirical support that more family income, earned on average by highly educated parents, stimulate further schooling economists put the emphasis on nurture in determining educational outcomes.

Alternatively, 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]

In this paper we compare both views. Our aim is 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 both family income and ability (measured as IQ test scores) move across generations, and we show what happens to the mobility of human capital if we embrace the idea that part of ability is hereditary.

There are three possible strategies to separate the effects of family environment from the genetic effects. The first and most perfect strategy would be with data on identical twins reared apart in different and unrelated families. Genetic differences would be controlled for, and environmental components would be identified. In practice, however, there are too few reliable cases. And even if there are some identical twins raised separately in different families, it is unlikely that the assignment to these families is a random process. The second strategy is to look at environmental influences shared by relatives raised together and apart. Controlling for the genetic structure between relatives, the differences between relatives raised in different families is used to measure the environmental impact of schooling. Since data is much more available, the second strategy dominates the empirical literature on the relative importance of genes and environment for a child's educational attainment (Taubman, 1976; Behrman and Taubman, 1989;

[2] Their views expressed in *The Bell Curve* have been widely criticized. 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 (Ashenfelter and Rouse, 1999; Currie and Thomas, 1995; Cawley, Heckman and Vytlacil, 1998; Goldberger and Manski, 1995; Korenman and Winship, 1995). In fact, these discussions are not new either and very much resemble the IQ debate that took place in the early seventies (Jensen, 1973; Herrnstein, 1973; Jencks, 1972).

Behrman, Rosenzweig and Taubman, 1994). The main conclusion is that schooling is mostly in the genes. One of the fundamental flaws, however, relate to the fact that raising relatives not only transmit related genes but also provide for related environments in which children are brought up. Since it is not clear how family environments of relatives in different families are related, resulting nature estimates are biased, and in most situations too high (Goldberger, 1978). The third strategy, which will be the strategy applied in this paper, compares children that are their parents' own offspring to children that are adopted. Since adopted children are genetically unrelated to the families that raise them, we control for the family environment in which children (both adopted and biological) are raised together, and thereby identify the genetic component.

Note that the strategy we've chosen is not perfect either. In fact, analyses on samples of adopted children and adopting families are often plagued by problems. Factors, like small sample size, missing relevant information on the biological background of adopted children, or potential matching strategies of adoption agencies, et cetera, affect the accuracy of our outcomes. As a matter of fact we do not have access to an ideal dataset, where all these pitfalls are accounted for. We have at our disposal a U.S. dataset, the Wisconsin Longitudinal Survey (WLS), that contains very detailed multigenerational information about households. Data collection started in 1957 on a group of high school students aged 16 years old 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, family conditions and the school careers of their children. Again, to shed light on the importance of the heritability of ability, we use information whether these children are adopted or not. At the end of the paper we shall return to the issue that our sample of adopting families and adopted children is not perfect either, and that to the extent that data are not missing at random, our outcomes are biased.

Still the present study has three clear advantages over previous economic studies of Taubman (1976), Behrman and Taubman (1989), and Behrman, Rosenzweig and Taubman (1994) who all 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. 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 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.[3]

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 detail. Section 5 presents and discusses our empirical findings. In Section 6 we examine the potential dangers of using data on adopted children and adopting families and their effects on our nature and nurture estimates. And finally, Section 7 summarizes our conclusions.

The main conclusion of the paper is that parental ability measured as IQ is an important factor in explaining the children's school success. IQ, however, is not the only mechanism. A portion of the transmission channel runs through family income as well. If we decompose the IQ transfers from parent to child into a genetic and environmental component, we find that about 80 percent of the ability effect relevant for school achievement measured by IQ is determined by nature. The genetic component drops to 65 percent as soon as we, instead of treating income as a mere environmental variable, recognize that ability is indirectly transmitted through income as well. In both situations nurture does not seem to 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

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

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

$$e_t = b_0 + b_1 e_{t-1} + v_t \tag{2.2}$$

[3]The 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.

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

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

Like v, w is considered random variation. The disturbances u, v and w have zero means and are assumed to be temporally uncorrelated.[4] 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

$$h_t = c_0 + b_0 c_2 + c_1 y_{t-1} + b_1 c_2 e_{t-1} + w_t + c_2 v_t \tag{2.4}$$

In this paper we focus on ability transfers, and particularly those parts that are passed on through genes and environment. Owing to the data at hand, we shall further assume that ability is wholly determined by IQ. We do know that this is a simplification. Ability measured as IQ test scores is only incompletely measured, is subject to measurement error, and varies during the development of the child (Plug, van Praag and Hartog, 1999). For now, however, it serves as an interesting starting point for the exercise to be developed in this paper.

To measure the importance of the heritability of IQ, we introduce 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 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:

$$e_t = b_0 + (b_1 - b_{g1}\delta_t) e_{t-1} + b_{g1}\delta_t e^*_{t-1} + v_t \tag{2.5}$$

Since the coefficient b_1 represents both genetic and cultural transfers, b_{g1} accounts for genetic transmission only. Since we do not observe abilities of the natural parents of adopted children, we replace $b_{g1}\delta_t e^*_{t-1}$ with $b^*_0\delta_t$ to correct for this omission. In effect, $b^*_0\delta_t$ then measures the average value of $b_{g1}\delta_t e^*_{t-1}$ across the subsample of adopted children. Inserting (2.5) into (2.3) yields a human capital function suitable for a sample of both biological and adopted children:

$$\begin{aligned} h_t = {} & c_0 + b_0 c_2 + b^*_0 c_2 \delta_t + \\ & c_1 y_{t-1} + b_1 c_2 e_{t-1} - b_{g1} c_2 \delta_t e_{t-1} + w_t + c_2 v_t \end{aligned} \tag{2.6}$$

Under the assumption that our functional form is correct estimates of $b_1 c_2$ and $b_{g1} c_2$ produce our nature and nurture estimates where a simple division $b_{g1} c_2 / b_1 c_2$ disentangles environment from genes.

[4] Goldberger (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.

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, gender, or being being an adopted child. Examples of attributes that vary across families are family income, parental ability and the number of siblings within the family. 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

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

where

$$\beta_k = \beta + \eta_k \tag{3.2}$$

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

$$h_{ik} = \alpha' z_{ik} + \beta' z_k + \epsilon_{ik} \tag{3.3}$$

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

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

and variance is defined by

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

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

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

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:[5]

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

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

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

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

The use of exponentiation ensures positive values both for the variance σ_{ik}^2 and the correlation ρ_k.[6]

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

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

where $\phi_2(.,.,\rho_k)$ 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

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

where ϕ_1 is the univariate standard normal pdf, and where

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

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

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

[6] Individual 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.

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

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

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.[7] 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. Through 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 genetic 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 students' 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

[7]High-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.

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 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 would cause the results to be biased. This holds true especially for the age variable because in that case only low achieving young children would 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: ability and financial. We discuss each group in turn. Our ability variable is the respondent's IQ score at age 16. Financial variables included in our analysis are family income measured in 1992 and in 1975. Since income is positively correlated with ability, we need an ability-free income measure to separate income effects from ability effects. Through a procedure outlined in detail in Appendix A, we identify an income component that is not correlated with observed or even unobserved ability.

The number of original observations 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. Thus, we exclude all childless and one-parent families and are left with a sample of about 6700 standard families. Of these, about 1350 observations had to be removed from the analysis due to missing (or incomplete) information on the family income measures in 1975 and 1992, and 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 1. 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. The first column of Table 2 presents estimates of equation (2.4). Among family-level variables we find, not surprisingly, that high income 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.[8] 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. 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. Having brothers or sisters has a negative effect on the educational attainment of children. The parameter estimate on the adoption dummy variable indicates that, on average, adopted children receive 8 to 9 months less schooling than children who are raised by their natural parents. Results do not change when we replace 1975 family income with family income measured in 1992.

5.1 Is it nature or nurture that matters?

To isolate that part of IQ that stems from genetic transmission we need to include the IQ $\times$ adoption interaction effect. This is done in the second column in Table 2 where we estimate equation (2.6). The interaction effect turns out to be negative, which corresponds with the idea that intelligence measured as childhood IQ is to a certain extent inherited. Note however that these effects are barely significantly negative. 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.

If we assume that our model is correctly specified, 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, $b_1 c_2$. The parameters of the interaction effect "IQ of parent $\times$ being

[8] We assume both parents to be in the same IQ class.

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. To be precise, according to these estimates, 79 percent of all ability transfers run through genes. Again, results do not change when 1992 family income is used. Compared to Jensen (1972, 1973) and more recently Behrman and Taubman (1989), 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. However, as we show in the next section, this percentage estimate needs be revised downward.

5.2 Are income effects merely environmental?

Up to this point we have treated income as an explicit environmental variable. Whether this is correct is questionable, since ability effects may operate through income as well: it should be expected that more able parents earn higher incomes. To find out whether these specific ability effects influence our nature and nurture estimates, we need to identify that part of income that is unrelated with parental ability and use this new income measure in our analysis instead of family income itself. Appendix A shows how we isolate that component of income that is unrelated with parental ability.[9]

In the final column of Table 2 both ability-free income components enter into the children's human capital equation as a parental income measure. We observe that parental income effects fall both in 1975 and 1992 but remain significantly different from zero. We also find that the influence of IQ increases since it picks up that part of income that is generated by it. The size of the genetic component ($b_{g1}c_2$) remains the same. The constancy of $b_{g1}c_2$ is striking: it points to a genetic transfer of a particular magnitude. The increase in b_1c_2 shows that a portion of the income effect comes from a cultural/environmental transfer of IQ, namely a channel that works through income. Consequently, if one is willing to assume that we have explored the full range of transmission effects here, the proportion of IQ that is genetically transmitted is about 65 percent (the ratio of $b_{g1}c_2$ over b_1c_2).

5.3 Distinguishing sons and daughters

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

[9] For a more detailed exposition on how we identify ability-free income measures we refer to Plug and Vijverberg (2000). That paper examines the influence of transitory and permanent income on the educational attainment of children.

the same time allowing for common family heterogeneity factors). This is what we do in Table 3. Results are as follows.

In panel A, 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 genetic impact is much higher for girls than it is for boys, differences are not statistically significant. Entering the ability free component of 1975 income (second column) reduces the income effects and raises IQ effects. Our estimates show this time that the genetic transfer amounts to 42 percent for boys and 90 percent for girls. By not treating 1975 income as an explicit environmental variable the nurture component of parental IQ compensates for the falling impact of parental income.

Panel B of Table 3 repeats the analysis with 1992 income. Parental IQ effects remain similar, and income effects become somewhat larger for sons. Our nature estimates show this time that with respect to IQ transfers and educational outcomes 44 percent run through the genes for boys. Our 102 percent estimate for girls shows that it is all genetics. With 1992 income that is unrelated with parental ability, the nature components 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 reported in Table 2 are statistically identical (the critical value is set at 14.1). Hence, none of the four different specifications is able to reveal that boys and girls are impacted 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

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

which implies that the human capital function reads as

$$\begin{aligned} h_t = {} & c_0 + b_0c_2 + c_1y_{t-1} + \\ & b_1c_2e_{t-1} - b_{g1}c_2\delta_t e_{t-1} + b_{g1}c_2\delta_t e^*_{t-1} + w_t + c_2v_t \end{aligned} \tag{6.2}$$

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. Low-income households and young single mothers 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

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

  For children adopted at a later age, say a_t, the term $b_{c1}\delta_t e_{t-1}$ should be replaced by $b_{c1}\delta_t f(a_t)e_{t-1}$, where $f(a_t) < 1$ for $a_t > 0$ and declining with a_t. However, a_t is not recorded in the survey. Thus, 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 the average of $b_{c1}f(a_t)$ across all adopted children. 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 term $(b^*_{c1} - b_{c1})\delta_t e_{t-1}$. For adopted children, this term is negative, implying that our estimate of the genetic effect is biased upwards. For children who were just brought into 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 of 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, and so forth, 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 there exists perfect assortative matching, the family's ability component e_{t-1} would be "identical" to e^*_{t-1}, implying that the nature effect would compel adopted children to attain as much schooling as biological children. 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.

  In the case of imperfect assortative matching mechanism, fortunate families will tend to adopt children with a higher ability. Thus, 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 ratio b_{g1}/b_1 may be interpreted as a nature effect on the condition 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 through adoption dummies in (2.6).[10] However, if these differences in upbringing are captured in the estimate of b_{g1}, 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 the nature estimate are the following. If parents invest less in their adopted children nature effects will be overestimated; if parents invest more in their adopted children the effects are reversed.

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

Let us examine the things we do know. Table 4 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. First, in regard to individual variables, adopted children are typically 2.4 years younger, and, as a consequence, are more likely to be in school still. Their schooling attainment is less (but since this variable is more likely censored among adopted children, such a comparison is a bit flawed). Since the WLS is a cohort survey, this also implies that adopting parents 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 4.

With respect to family background variables we find significant differences too. Adopted children live in higher-income households with fewer siblings and higher-IQ, better educated parents. Adopting families turn out to be above average in all their socioeconomic characteristics. The structural differences in the socioeconomic characteristics of biologically related and adopting families

[10] In 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.

suggest that either adopting agencies or adopting families are selective. Yet, even though observed differences in individual and family characteristics are favorable for the human capital accumulation of adopted children, recall that the estimates in Table 2 show that adopted children remain worse off with respect to schooling attainment 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 realistic, and that our nurture estimate of 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 5 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 2 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 6. The parameter estimates do not differ much compared to those presented in Table

2, with one exception, namely that this time all relevant adoption parameters significantly differ from zero.[11] 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 65 percent statistic may be viewed as an upper bound of our nature estimates. The observation that nature is more dominant in explaining schooling differences remains.

7 Concluding remarks

The intergenerational mobility literature shows persistently that children raised in highly educated families are more educated than children raised in less 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 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 if we equate family income with environment, about 80 percent of the ability effects relevant for school achievement can be attributed to genetic effects. However, parental ability effects work through family income as well. Purging contributions of ability to the measured family income causes the genetic ability transfer percentage to drop to 65 percent. 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 three things: (i) that it is only to a certain extent that ability is an important factor in explaining the educational attainment of children; (ii) but that the largest part of ability relevant for education is inherited; and (iii) 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

[11] In the sample used for Table 2, 114 children were adopted. Here, 545 children are adopted, which accounts for the relatively greater increase in precision of the adoption parameters.

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.

Appendix A

We extract ability-free 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; these equations are reported in Table A1. For both years, we compute residuals. These now consists of two components: unobserved parental ability and a non-structural part (which might be income generated by luck in the market). If one assumes that unobserved parental ability measures are correlated, and that non-structural 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 ability-free. And vice versa, if we regress the 1975 residual on our 1992 measure we obtain a measure for ability-free income generated in 1975. The equations from which the ability-free components are derived may be found in Table A2. 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." Note furthermore that our ability-free income measure 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.

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Table 1: Descriptive statistics, means and standard deviations

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

Standard deviations in italics

Table 2: Education and nature and nurture effects of parental ability

A: Using income measured in 1975

years of education						
intercept	5.978	*0.651****	5.937	*0.652****	13.614	*0.317****
daughter	0.154	*0.056****	0.154	*0.056****	0.154	*0.057****
age	-0.112	*0.007****	-0.112	*0.007****	-0.114	*0.008****
IQ of parent	0.361	*0.023****	0.365	*0.023****	0.412	*0.023****
log income 1975	0.828	*0.064****	0.829	*0.064****		
log ability-free income 1975					0.281	*0.073****
number of siblings	-0.176	*0.022****	-0.175	*0.022****	-0.201	*0.022****
being adopted	-0.713	*0.315***	2.259	*2.330*	2.259	*2.280*
being adopted×IQ of parent			-0.289	*0.226**	-0.285	*0.223**
variance of years of education						
individual component						
intercept	1.206	*0.025****	1.205	*0.025****	1.207	*0.025****
daughter	-0.173	*0.033****	-0.172	*0.033****	-0.168	*0.035****
being adopted	0.432	*0.109****	0.380	*0.108****	0.386	*0.116****
family component						
IQ of parent	0.115	*0.040****	0.116	*0.040****	0.079	*0.009****
log income 1975	-0.053	*0.046*	-0.053	*0.046*		
log ability-free income 1975					0.044	*0.109*
number of siblings	-0.099	*0.040****	-0.099	*0.040****	-0.119	*0.037****
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	

A: Using income measured in 1992

years of education						
intercept	5.771	*0.569****	5.743	*0.569****	13.595	*0.316****
daughter	0.159	*0.056****	0.160	*0.056****	0.157	*0.057****
age	-0.104	*0.007****	-0.104	*0.007****	-0.112	*0.007****
IQ of parent	0.317	*0.023****	0.320	*0.023****	0.412	*0.023****
log income 1992	0.773	*0.047****	0.773	*0.047****		
log ability-free income 1992					0.369	*0.057****
number of siblings	-0.182	*0.021****	-0.181	*0.021****	-0.207	*0.022****
being adopted	-0.744	*0.302****	1.836	*2.227*	2.055	*2.265*
being adopted×IQ of parent			-0.251	*0.216*	-0.266	*0.221*
variance of years of education						
individual component						
intercept	1.201	*0.025****	1.200	*0.025****	1.202	*0.025****
daughter	-0.199	*0.034****	-0.198	*0.034****	-0.175	*0.036****
being adopted	0.377	*0.117****	0.334	*0.116****	0.380	*0.119****
family component						
IQ of parent	0.139	*0.040****	0.139	*0.040****	0.080	*0.009****
log income 1992	-0.065	*0.039**	-0.065	*0.039**		
log ability-free income 1992					0.059	*0.066*
number of siblings	-0.115	*0.038****	-0.115	*0.038****	-0.122	*0.037****
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 3: Education, nature and nurture effects for sons and daughters

A: Using income measured in 1975

years of education of boys				
intercept	6.154	*0.927******	13.827	*0.432******
age	-0.117	*0.010******	-0.119	*0.010******
IQ of parent	0.368	*0.032******	0.416	*0.032******
log income 1975	0.828	*0.091******		
log ability-free income 1975			0.270	*0.099******
number of siblings	-0.151	*0.030******	-0.178	*0.030******
being adopted	1.513	*2.239*	1.209	*2.359*
being adopted×IQ of parent	-0.202	*0.218*	-0.177	*0.231*
years of education of girls				
intercept	5.746	*0.890******	13.495	*0.444******
age	-0.104	*0.011******	-0.106	*0.011******
IQ of parent	0.363	*0.032******	0.410	*0.032******
log income 1975	0.836	*0.087******		
log ability-free income 1975			0.297	*0.098******
number of siblings	-0.202	*0.032******	-0.227	*0.032******
being adopted	2.760	*4.203*	3.117	*4.006*
being adopted×IQ of parent	-0.347	*0.407*	-0.371	*0.390*
variance of years of education				
boy component				
intercept	1.043	*0.029******	1.048	*0.030******
being adopted	-0.237	*0.498*	-0.153	*0.492*
girl component				
intercept	1.196	*0.025******	1.198	*0.025******
being adopted	0.692	*0.144******	0.684	*0.150******
family component				
IQ of parent	0.118	*0.041******	0.079	*0.009******
log income 1975	-0.056	*0.046*		
log ability-free income 1975			0.026	*0.111*
number of siblings	-0.099	*0.041******	-0.120	*0.038******
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 3 continued:

B: Using family income measured in 1992

years of education of boys				
intercept	4.788	*0.777****	13.772	*0.427****
age	-0.105	*0.010****	-0.116	*0.010****
IQ of parent	0.309	*0.032****	0.415	*0.032****
log income 1992	0.880	*0.065****		
log ability-free income 1992			0.454	*0.077****
number of siblings	-0.155	*0.029****	-0.186	*0.030****
being adopted	0.810	*2.205*	0.784	*2.343*
being adopted×IQ of parent	-0.137	*0.214*	-0.135	*0.229*
years of education of girls				
intercept	6.696	*0.784****	13.487	*0.444****
age	-0.101	*0.011****	-0.106	*0.011****
IQ of parent	0.330	*0.032****	0.410	*0.032****
log income 1992	0.673	*0.066****		
log ability-free income 1992			0.295	*0.077****
number of siblings	-0.210	*0.031****	-0.232	*0.031****
being adopted	2.644	*3.970*	3.141	*3.946*
being adopted×IQ of parent	-0.337	*0.385*	-0.373	*0.384*
variance of years of education				
boy component				
intercept	1.006	*0.029****	1.035	*0.030****
being adopted	-0.215	*0.449*	-0.150	*0.447*
girl component				
intercept	1.190	*0.025****	1.193	*0.026****
being adopted	0.614	*0.151****	0.672	*0.153****
family component				
IQ of parent	0.136	*0.041****	0.080	*0.009****
log income 1992	-0.062	*0.041**		
log ability-free income 1992			0.087	*0.073*
number of siblings	-0.116	*0.039****	-0.124	*0.038****
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 4: Descriptive statistics of biological and adopted children

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

Table 5: Adoption families and selection effects: estimates of a logit model

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

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

Table 6: Education and nature and nurture effects using all children in the full WLS sample

A: Using family income measured in 1975

years of education				
intercept	6.735	*0.433******	13.873	*0.218******
daughter	0.173	*0.040******	0.171	*0.040******
age	-0.113	*0.005******	-0.116	*0.005******
IQ of parent	0.326	*0.014******	0.372	*0.014******
log income 1975	0.772	*0.041******		
log ability-free income 1975			0.301	*0.045******
number of siblings	-0.161	*0.012******	-0.179	*0.012******
being adopted	1.768	*0.745******	1.736	*0.755******
being adopted×IQ of parent	-0.246	*0.071******	-0.239	*0.071******
Mean loglikelihood	-1.774		-1.785	
N	13626		13626	
genetic component in ability (b_{g1}/b_1)				
nature effects	0.754		0.642	

B: Using family income measured in 1992

years of education				
intercept	6.561	*0.380******	13.886	*0.217******
daughter	0.174	*0.039******	0.172	*0.040******
age	-0.107	*0.005******	-0.115	*0.005******
IQ of parent	0.286	*0.015******	0.370	*0.014******
log income 1992	0.722	*0.031******		
log ability-free income 1992			0.318	*0.036******
number of siblings	-0.163	*0.012******	-0.184	*0.012******
being adopted	1.539	*0.740******	1.599	*0.754******
being adopted×IQ of parent	-0.225	*0.070******	-0.226	*0.071******
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

Table A1: Estimating ability-free income measures in 1975 and 1992, part I: Estimating family income using observed ability and human capital characteristics

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

Table A2: Estimating ability-free income measures in 1975 and 1992, part II: Estimating ability-free income using unobserved ability and human capital characteristics

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

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

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