Aalto University
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Adoptee studies and transmission of education

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AALTO UNIVERSITY SCHOOL OF ECONOMICS ABSTRACT

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ADOPTEE STUDIES AND TRANSMISSION OF EDUCATION

Objectives of the Study

The heritability of education has been documented in numerous studies in different countries. Statistically, children of parents who have more years of education are also themselves more likely to obtain more education. This creates unequal opportunities which are possible inefficiencies in the educational market. The transmission of education from parents to children might work through nature, nurture or the combination of the two. One of the strategies to find out what are the effects of nature and nurture in transmission of education is to study families with adopted children. The objective of this study is to determine what current adoptee studies tell us about the effects of nature and nurture on educational attainment.

Academic background and methodology

The major part of the study is a literature review. Literature review defines the concept of "transmission of education" and introduces the intergenerational regressions used in estimating the degree of heritability of the outcome of interest. The findings of the major adoptee studies which estimate intergenerational regressions are summarized. In addition, the assumptions required for internal and external validity of these studies are discussed.

The empirical part is an estimation of intergenerational regression for education of adopted and non-adopted children. The study replicates some of the results published in Sacerdote (2007).

Findings and conclusions

The reviewed studies find that intergenerational transmission of education is lower for adoptees compared to non-adoptees. With the assumption that the models are correctly specified, the estimates on how much family inheritable endowments contribute to the intergenerational schooling association range from 30 to 80 percent, but the majority of estimates are close to 50 percent. These percentages are inclusive of educational attainment passed through the assortative mating. The estimates obtained in empirical study are very close to estimates published in Sacerdote (2007) for mother's education and indicate positive and statistically significant effect of home environment when estimated for mother's education. At the same time, I find a statistically significant effect of father's education on adoptees' education.

The analysis also shows that the adoptee studies that estimate the intergenerational transmission of education are of limited practical use to policymakers, since their generalizability to general population is questionable and they do not have power to predict the effects of possible policies and interventions.

Keywords: transmission of education, adoptee studies, intergenerational regression, nature and nurture

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1. Introduction

1.1. Nature versus nurture debate

One of the oldest issues in social sciences is the relative influence of nature and nurture on various individual outcomes, in this context, nature referring to genetically inherited traits and nurture referring to the rearing environment. In its essence, the debate focuses on the relative contributions of genetic inheritance and environmental factors to human development.

We know that some characteristics are determined purely biologically (genetically), for example eye color, skin color, hair color and certain genetic diseases. Other characteristics have very strong biological component, but environmental factors also play a role. For example, from our everyday experience we know that genetic factors play a major role in determining height, but that nutrition is a particularly important environmental factor. In order to answer the question of relative importance of nature and nurture scientifically, the question is rephrased as: "How much variation (difference between individuals) in individual outcome (height, for example) is attributable to genetic effects and how much is attributable to nutritional effects?" In case of height, the answer to this question is that about 60 to 80 percent of the difference in height between individuals is determined by genetics, whereas 20 to 40 percent can be attributed to environmental effects, mainly nutrition. This aggregated result comes from studies that measure the proportion of the total variation in height due to genetic factors. The results differ to some extent across geographical regions and countries; for example, the study of 8,798 pairs of Finnish twins indicated that heritability accounted for 78 percent in variation for men and 75 percent in variation for women (Silventoinen et al. 2000). Thus, we can say that genetics doubtlessly plays the major role in human height and that nutrition is an important environmental factor. What can we say about more complex characteristics, such as characteristics related to human behavoir?

Some philosophers such as Plato and Descartes proposed that certain things are inborn, or that they simply occur naturally and are not in any way subject to environmental influences. This viewpoint assumes that all the behaviour is the result of genetically passed treats, and favours nature in the *nature versus nurture* debate. The opposite viewpoint assumes that our behaviour is the result of our rearing environment, experience and learning during lifetime. Well-known thinkers such as John Locke believed in what is known as *tabula rasa*, which translates from Latin as “blank slate”.

According to this notion, individuals do not possess any inborn mental characteristics, and our personality, social and emotional behaviour are determined by our experience.

During the last decades, there has been a growing interest among social scientists and economists about the processes that explain why children turn out the way they are. Social scientists have enquired into origins of various social and behavioural characteristics. Along this line of research, economists have been studying outcomes such as educational attainment, occupation, income levels. Also certain life choices have been studies, such as nonmarital motherhood or welfare recipiency in young adults. The main goal of these inquires is to establish relationships between various inputs, like different aspects of the family and neighbourhood environment, and observed outcomes. The typically considered inputs are genetically transferred endowments and rearing environment, which is commonly divided into family environment and neighbourhood environment. For example, how person succeeds in education can be tied to inherited abilities or influenced by parenting style.

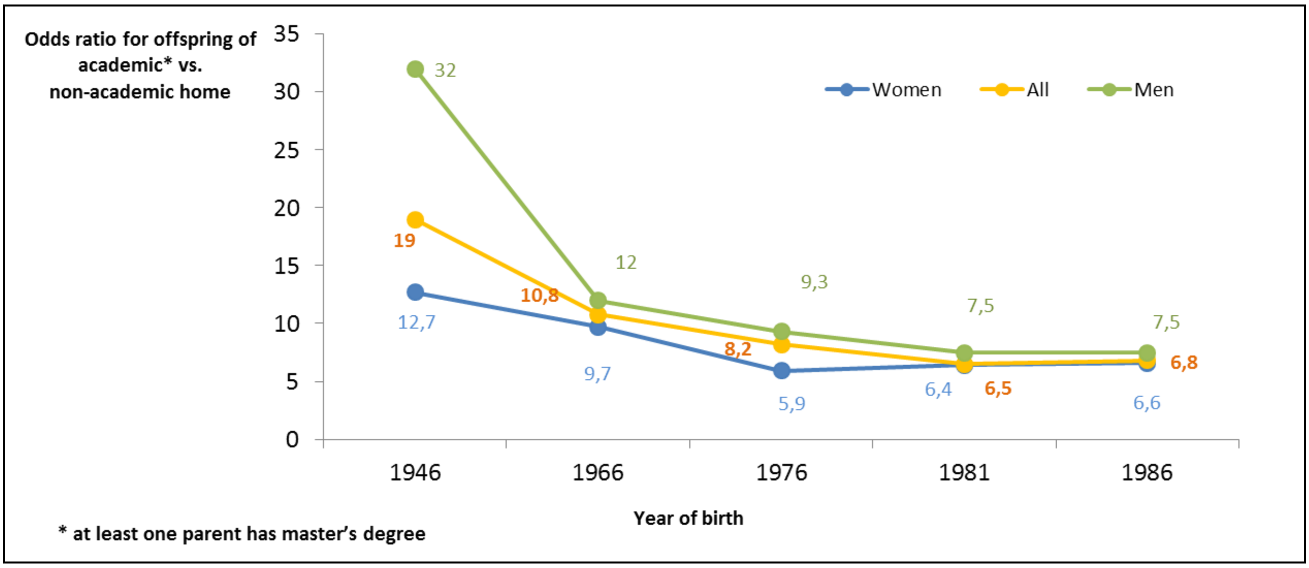
However, the more complex the studied outcome is, the more challenging it becomes to make a meaningful separation of genetics from environment and to gain understanding of which environmental factors matter. It is broadly recognized that in case of complex social outcomes such as educational attainment or occupational success, genetic and environmental influences work together and interact, making it literally impossible to directly observe the pure effects of separate factors.

1.2. Intergenerational associations in educational attainment

There is rapidly growing body of economic research that explores the relationship between socioeconomic status of parents and their children. Especially links between parental income and children's income as well as parental education and children's education are being extensively studied in many countries. A large pool of research finds substantial intergenerational associations in earnings and income (Björklund et al. 2006). Several studies have found some cross-national differences with weaker intergenerational associations in Scandinavian countries and stronger associations in US (Solon 1999). The standard approach in these studies is to regress children's outcomes on those of their parents. Studies of intergenerational transmission of income are reviewed by Björklund and Jäntti (2008). Scope of this work is narrowed down to the intergenerational transmission of education.

The studies have repeatedly found that children of parents who have more years of education and higher degrees get more education comparing to children whose parents are less educated. Kivinen et al. (2012) studied heritability of education in Finland among children born in 1986. They found that those children who were born into families where at least one parent had academic degree were much more likely to go to university comparing to children whose neither parent had academic degree. Figure 1 summarizes the results published in Kivinen et al. (2012). It shows the ratio of probabilities of getting high education for children from academic[1] homes versus children from non-academic homes, for children born in 1946, 1966, 1976, 1981 and 1986. Ratio of 6,8 means that child who comes from academic home will get higher education with probability that is 6,8 times higher than the probability of getting higher education for child who comes from non-academic home. As can be seen from Figure 1, children chances for higher education have become more even, but the difference is still striking.

Figure 1. Differences in participation in university studies according to family background



Source: based on Kivinen et al. (2012)

The estimates of heritability of educational achievement vary depending on the country and the method of measurement of educational achievement. For example, educational achievement can be measured in years of education or in terms of college/university attendance. In the latter case there is no distinction between bachelor and master's degree. Recent studies have found some difference among countries: Scandinavian countries seem to have weaker intergenerational associations, and United States stronger intergenerational associations (Björklund et al. 2006). However, overall it is clear from empirical evidence that there are substantial intergenerational associations in education

[1] At least one parent has university master's degree

and economic status (Solon 1999). Moreover, Haveman and Wolfe (1995) in their literature review on the determinants of children's educational attainments conclude that the education of parents is probably the most fundamental factor in explaining the child's success in school.

There is solid body of research on heritability of education and the strength of the links between parental education and education of their children. The concept of "intergenerational transmission" of education (or of educational attainment) has being widely used. Intergenerational transmission of education refers to the link between parental education and education of children within a given family and measures the association between parental and children's education. Studies of intergenerational transmission of education estimate how one additional years of education for a parent – father or mother – impacts child's years of education. Commonly cited result is that each year of education of parent is associated statistically with one quarter of a year more education for the child, whereas parents having college education increases likelihood of child having college education by 25 percent (Björklund et al. 2004).

Studies in this field have recently started to make a distinction between intergenerational associations and intergenerational causal effects. Intergenerational associations refer to the correlation between parental education and education of their children, without specifying what the mechanisms behind this correlation are. Studies of intergenerational associations seek to quantify the relationship between parental education and education of their children. The strong intergenerational associations found in these studies have urged scientists to inquire about the forces which are responsible for these intergenerational associations.

1.3. Understanding mechanisms behind intergenerational associations

Economists are interested in better understanding how the production function of education works and what causes intergenerational associations in educational attainment. According to Björklund et al. (2004), there are three main reasons why these issues are of importance to economists. Firstly, economists ask whether the current situation in educational market is efficient, and, if not, how it can be improved. Secondly, there is issue of equity: the strong transmission of education from parent to children education raises questions about equality of life chances in terms of education. And, finally, economists, and especially policymakers, are interested in educational spillovers on the next generation. If educational policies produce externalities in the form of education of the next generation, these externalities should be taken into account when designing educational policies. In addition to these, intergenerational effects of human capital are also relevant for some versions of modern growth theory (Benabou 1996, Aghion & Howitt 1998).

Three major approaches have been used in the literature in order to address the role of different factors responsible for educational achievements: behavioural genetics approach, computation of intergenerational associations for adoptees and instrumental variables. Behavioral genetics approach is related to the earlier discussed *nature versus nurture* framework. Various studies have estimated what proportion of total variance in educational attainment is attributed to nature, and what proportion is attributed to nurture (references). As Plomin (2001) notes, adoption and twinning provide experimental situations that can be used to test the relative influence of nature and nurture. Thus, the studies utilize the fact that identical twins share the same set of genes, whereas non-identical twins have 50 percent of their genes in common. The inference about relative importance of nature and nurture is made from analyzing how much more identical twins resemble each other comparing to non-identical twins. This is done by comparing variance in educational outcomes for identical twins to variance in outcomes for non-identical twins. Another strategy is to use data on adopted children and their siblings: studies of adoptees compare how much more full siblings resemble each other comparing to two siblings one of which has been adopted. Higher resembles between full siblings would is interpreted as being caused by genetic factors. Studies of variance decomposition are of interest to academics and general public. However, information on relative role of genetics and rearing environment in educational attainment is of limited practical use to policy makers. For example, finding that certain outcome has a large genetic component does not necessarily imply that there is no room for policy intervention: Goldberger (1979) uses eyeglasses as an example of policy that mitigates genetic effects. Thus, variance breakdown is not informative in terms of designing intervention policies.

Another approach to understand the mechanisms responsible for educational attainment is through an attempt to measure directly the intergenerational causal effect of different inputs. These inputs can be, for example, parental socioeconomic status, parental education or income. This strategy relies on use of adoptee data: adoptees do not share their adoptive parents' genes, and thus it is claimed that association between adoptee's education and education of their adoptive parents is a direct measure of parental input (upbringing). In addition to measuring parental input, some studies attempt to capture the intergenerational causal effect of education. These studies are practically asking *"to what extent educational achievements of young adults are caused by educational attainments of their parents"*. Another way to put this idea is to ask whether directly increasing parental education would automatically result in increased education of their children. Answering this question would allow better understanding of the direct role of parental education in observed intergenerational associations, which is obviously of a great value to policy makers.

The third approach relies on use of instrumental variables (IV). In this line of research, educational reforms that are related to years of compulsory education and implemented gradually throughout a country's regions are used as instrumental variables. The strategy relies on comparing educational outcomes of children of parents with differing years of education resulting from the fact that parents of different children come from variety of regions within a country.

This work belongs to the group of studies that utilize the second approach for separating the role of various environmental effects from the role of genetic effects on educational achievement. It provides critical review of results obtained in studies which focus on intergenerational transmission of education for adoptees. In addition, it offers a modest contribution to the existing empirical results.

1.4. Purpose and scope of the study

The goal of the study is to explore the current understanding about the causal effect of upbringing and causal effect of parental education. The scope is narrowed down to studies of intergenerational association in schooling of adoptees and their adoptive (or biological) parents. The issue is addressed through a literature review and an empirical study.

The literature review covers the main adoptee studies of intergenerational transmission of education and explores results of these studies as well as interpretation of those results and conclusions that can be made from them.

The empirical part consists of replicating the previously published results and a small contribution to existing results on intergenerational transmission of education. The study is made on a dataset of Korean – American adoptees that were adopted from Korea into families in United States as a part of Holt program. This data was used in a study made by Sacerdote (2007) and is publicly available on his webpage[2]. Results on intergenerational transmission of education for adoptees and their adoptive mothers obtained by Sacerdote (2007) are replicated and also extended to include results on intergenerational associations between education of adoptees and their adoptive fathers.

[2] "Public Use Data Set of Adoptees", accessed at: http://www.dartmouth.edu/~bsacerdo/

2. Concepts and methods

2.1. Intergenerational transmission of educational attainment

Intergenerational transmission of education refers to the link between parental educational attainment and child's educational attainment. It is considered to be a measure of educational mobility in a society, and high intergenerational persistence of educational attainment is considered to be a sign of existing barriers to equal opportunities in job market and, consequently, in income levels (Black & Devereux, 2010).

Technically, educational attainment is typically measured in years of schooling or in terms of college attendance. Extensive studies have shown that there is a strong link between parents' and child's years of education and college attendance status. The intergenerational transmission of education can be measured by parent-child correlation coefficient or by the regression coefficient of child's educational attainment on parental education (Huang 2013). For example, parent-child correlation in years of schooling is about .60 in South America, about .40 in Western Europe, .46 in the US, and is the lowest in Nordic countries (Huang 2013). Recent literature on intergenerational associations in educational attainment relies mostly on regressing child's education on parental education. The obtained regression coefficient is often referred to as ”the transmission coefficient”.

2.2. Transmission coefficients

Transmission coefficients are a measure of magnitude of the link between child's education and parental education. Transmission coefficients are obtained by regressing child's years of education on parent's years of education and they show the strength of association between educational attainment for the parent and for the child. Transmission coefficient can also be measured for college attendance status, indicated whether person attended college or not, in which case transmission coefficient is calculated for dummies of college attendance status.

A typical model used in research on intergenerational transmission of educational attainment is of the following form:

$$Y_{ic} = \delta_0 + \delta_1 Y_{ip} + v_{ic} \quad (1)$$

where Yi represents years of education, subscript i indexes the family where the child has been born and raised, subscripts *bc* and *bp* denote biological child and parents. This regression estimates how many additional years (months) one extra year of parental education adds to child's education. The estimated coefficient δ_1 is the transmission coefficient and it measures the strength of intergenerational association for the children and their parents in the studied sample. Transmission coefficient shows how much increase in years of education of parents is transmitted into increase in years of education of their children. Thus, δ_1 shows by how much an additional year of education of mother (or father) increases child's years of education.

2.3. Model of intergenerational transmission of education

The strong intergenerational association in educational attainment of parents and their children does not necessarily reflect a causal relationship. Existing literature considers two main channels thorugh which the education is transmitted from parents to children. The first channel may be genetic: parents transfer their natural abilities to their children through genetic inheritance. The second channel may be related to nurturing environment which parents create for their children. There is also a distinct question of the causal effect of parental schooling to child's schooling, meaning that, would increasing parental education result in increased education of their children, net of the effect that parental education has on family income and resources. Studies of the transmission coefficient for adoptees and their adoptive and biological parents are designed to separate the effects of genetics from the effects of nurture.

Studies of intergenerational transmission of education on general population explore the association between parental and child education. However, this association does not indicate what factors and inputs matter for educational attainment. Data on adoptees allows taking the first step towards understanding what causes the intergenerational associations in educational attainment. Since adopted children share only their parents' environment and not their parents' genes, any relation between the schooling of adoptees and their adoptive parents is driven by the influence parents have on their children's environment, in other words, by the upbringing. Thus, studies of adoptees allow decomposing the estimated intergenerational effect (transmission coefficient) into component that measures the contribution of genetics and component that captures the effect of post-birth environment (nurture).

Studies estimating the influence of genetic and nurturing factors in intergenerational transmission of education use the following basic model describing impacts of different factors on child's educational attainment (Plug, 2004):

$$Y_{ic} = \alpha_0 + \alpha_1 Y_{im} + \alpha_2 Y_{if} + g_{im} + g_{if} + f_{im} + f_{if} + v_i \quad (2)$$

Here, Y_{ic} indicates the child's schooling, Y_{im} is mother's schooling, Y_{if} is father's schooling, g's are unobserved inheritable endowments of both parents, f's are also unobserved endowments that express child-rearing talent of both parents and v_{ic} is child-specific characteristic. Attention is focused on parameters α_1 and α_2 which measure the effect of parental schooling on that of their children.

For a child raised by biological parents, in regression of the form as in equation (1)

$$Y_{ic} = \delta_0 + \delta_1 Y_{im} + \delta_2 Y_{if} + v_{ic}$$

coefficient δ_1 and δ_2 captures the effect of education, but also the effect of g (unobserved genetic endowment) and f (parent's child-rearing talents).

For a child adopted into a family, the corresponding model for transmission of education is does not include transfer through genetic endowments, because adoptees do not share their adoptive parent's genes (Plug, 2004):

$$Y_{ic} = \alpha_0 + \alpha_1 Y_{iam} + \alpha_2 Y_{iaf} + f_{im} + f_{if} + v_{ic} \quad (2^0)$$

Therefore, when we estimate the OLS regression for adoptees of the same form as for own-birth children, the transmission coefficients are free from genetic endowments-driven bias:

$$Y_{iac} = \beta_0 + \beta_1 Y_{iam} + \beta_2 Y_{iaf} + v_{ic} \quad (3)$$

where coefficients β_1 and β_2 measure the effect of parental schooling on child's schooling, and include also the effect of parenting skills f_i, but exclude the effect of nature g_i. This is the essence of adoptee approach: transmission coefficient calculated for adoptees and their adoptive parents do not include inheritance-driven component, and thus are measures of impact of nurture on educational attainment.

It is common to estimate transmission coefficients for mother's and father's education in separate regressions, because existing studies of transmission of education on general population estimate separate regressions for fathers and mothers. Thus, estimating transmission coefficient for adopted children and their adoptive mothers and father in separate regressions provides better comparability with the existing studies on general population. However, it should be noted that there is correlation between education of parents (Y_{iam} and Y_{if}), and neither method is perfect: if we include both father's and mother's education into regression, we end up with the multicollinearity problem, if we include only one parent's education into the regression, the estimated regression coefficient for this parent's education is likely to overstate the true impact of his or her education on child's education.

Father's and mother's educational attainments are highly correlated because of the phenomenon known as assortative mating: there is positive selection in schooling on the marriage market, leading to positive correlation between father's and mother's educational attainment Y_m and Y_f. The correlations between spouses' years of education are on general as high as 0,4 – 0,5 (Holmlund et al. 2011). Since the correlation between Y_{im} and Y_{if} iz nonzero, the estimates of transmission of education are effectively biased if estimated in the same regression or in separate regressions. However, some studies aim to control for assortative mating applying various techniques, such as regressing child' education on sum of parental educations (Plug 2004, Björklund et al. 2006, and Holmlund et al. 2011).

Some studies make assumption of zero correlation between parental education Y_{ip} and child-rearing talents f_i. With this assumption, β_1 and β_2 in equation (3) are consistent estimates of α_1 and α_2 in equation (2^0), meaning that we obtain measures of direct effect of parental education on education of children. The claim is that since we control for genetic endowments and with the assumption that schooling is uncorrelated with child-rearing talent, the coefficient represent the pure and causal effect of parental schooling on child schooling. However, in reality we have no grounds to claim that there is no correlation between one's education and child-rearing talents. In fact, we simply do not know enough about this subject: as Holmlund et al. (2011) note, the correlation could be negative, zero or positive. Thus, β_1 and β_2 coefficients actually capture the effect of schooling and everything else that is correlated with the adoptive parent's schooling and has an independent effect on Y_{ic}, apart from the genetic endowments. Holmlund et al. (2011) suggest that, if we assume that parenting skills are positively correlated with schooling, then the estimated coefficients can be seen as an upper bound estimate of the intergenerational causal effect of an outcome Y. However, as Holmlund et al. (2011) continue, it is not a priori clear that the correlation between child-rearing talent and schooling is positive. Their argument is that, for example, if people who obtain more education focus relatively more on their career comparing to parenthood, the correlation could be negative. The other reason for negative correlation could arise, if, for instance, some mothers with lower parenting skills would prefer to focus on education and work career in the expense of motherhood. On the other hand, if increasing level of education makes one more informed as a parent and positively affects certain parenthood-related decisions, the correlation would be positive. Even assuming that child-rearing talents are not correlated with schooling, we cannot rule out that there are some other factors (rather than genetic and child-rearing talent) that are correlated with parental schooling and that have independent effect on child schooling. There seems to be general consensus in the literature that transmission coefficient for adoptees (β_1 and β_2) ought to be seen as estimates of impact of nurturing environment, and not estimates of direct impact of parental education on child's education.

In cases where data on biological parents of adopted children is available, it is possible to also directly estimate the magnitude of influence of genetic endowments *g*. The following regression can be estimated for adopted child and the biological mother of that child:

$$Y_{\mathrm{ic}} = \gamma_0^{m} + \gamma_1^{m} Y_{ibm} + v_{ic} \text{ (4)}$$

where γ_1^m captures the effect of genetic endowments from the model presented in equation (2). It is argued that in addition to purely genetic effect, γ_1^m actually also captures the effect of pre-natal environment. According to thus argument, transmission coefficient for biological mother's education for an adopted child can not be treated as purely representing the effect of genetics, but it represents the combined effect of genetics and pre-natal environment.

Study of BLP (2006)/check this! has data on biological fathers, and they estimate regression

$$Y_{ic} = \gamma_0^{f} + \gamma_1^{f} Y_{ibf} + v_{ic} \text{ (5)}$$

Björklund et al. (2006) argue that whereas the coefficient γ_1^{m} for a biological mother captures the effect of both genetic factors and pre-natal environment, it is reasonable to assume that biological father does not influence the pre-natal environment and his influence is limited to genetics. Thus, Björklund et al. (2006) suggests that coefficient γ_1^f captures the pure effect of genetics *g* from the original model of transmission of education (equation 2). Assuming that genetic effects of mother and father are equal in their magnitude, the difference between coefficients [γ_1^m- γ_1^f] represents the effect of pre-natal environment.

To sum up, using data on adoptees for estimating intergenerational transmission coefficients allows separating the effect of nature and nurture on educational attainment. Comparison of transmission coefficients estimated for adoptees and their adoptive parents to transmission coefficients estimated for general population shows how much of the transmission remains in the absence of genetic relationship between parent and child. This translates into question of how much upbringing (nurture) matters net of genetic effect (nature). Estimation of transmission coefficients for the education of biological parent of adopted children reveals how much of the transmission remains when biological parents are not involved in upbringing the child and how much genes (nature) matter for educational attainment.

2.4. Interpretation of transmission coefficients in adoptee studies

In order to interpret the transmission coefficients calculated in adoption studies as true estimates of the impact of family environment on educational attainment for general population, we need to make several assumptions about the samples studied and the model itself. These assumptions can be divided into those needed for correctly estimating transmission coefficients for adoptees in the studied samples, and those needed for generalizing the results on the whole population.

The core of the assumptions can be best explained by referring to earlier mentioned Equation 2, Equation 2^0 and Equation 3 (reprinted below):

$Y_{ic} = \alpha_0 + \alpha_1 Y_{im} + \alpha_2 Y_{if} + g_{im} + g_{if} + f_{im} + f_{if} + v_{ic}\,(2^0)$	*transmission model for general population*
$Y_{ic} = \alpha_0 + \alpha_1 Y_{iam} + \alpha_2 Y_{iaf} + f_{im} + f_{if} + v_{ic}\,(2)$	*transmission model for adoptees*
$Y_{iac} = \beta_0 + \beta_1 Y_{iam} + \beta_2 Y_{iaf} + v_{ic}\ \ (3)$	*the least-squares regression for adoptees*

Correctly estimating transmission coefficients for adoptees effectively means that transmission coefficients β_1 and β_2 estimated in regression for adoptees (equation3) are true estimates of the effect of schooling (α_1 and α_2) in the transmission model for adoptees (equation 2^0). Set of assumptions needed to satisfy this condition is called “internal validity assumptions” (Björklund et al. 2006, Holmlund et al. 2011).

Generalizing the results obtained for adoptees on the whole population implies showing that the results obtained for adoptees can be extrapolated on the whole population, that is, on families where parents and children are also biologically related. This means showing that the estimates of α_1 and α_2 in equation (2) can be interpreted as a consistent estimate of α_1 and α_2 in equation (2^0). Set of assumptions needed to satisfy this condition is called “external validity assumptions” (Björklund et al. 2006, Holmlund et al. 2011).

The theory on assumption is discussed below, and chapter X presents the summary of whether these assumptions hold in the reviewed studies.

2.4.1. Internal Validity

Assumptions needed for internal validity of adoption results are necessary to consistently estimate the intergenerational effect for adoptees using a sample of adoptees. In order to estimate a_1 and a_2

consistently in equation (2), we need to assume that (a) adoptees are randomly assigned to adoptive families (or they assigned in a way researchers are aware of and can control for (Björklund et al. 2006)) and that (b) children are adopted at birth. The existence of non-random assignment likely generates an estimate of the intergenerational transmission of education through nurture (β_1 and β_2) too high. If children are placed into their adoptive families with some delay after their birth, the estimate of nurturing environment's influence on education (β_1 and β_2) might be biased downwards. And if child-rearing talent f is related to parental education, the estimated β_1 and β_2 are biased either upwards or downwards, depending on the nature of the relationship.

a) Assumption of random assignment

Assumption of random assignment requires that adoptees are assigned to adoptive families in a random manner. This assumption is necessary to eliminate correlation between parental education and parental genetic endowments.

Adoption approach heavily relies on the idea that adopted children and their adoptive parents are not related genetically and that there is no correlation between their genetically determined abilities. However, one of the biggest challenges for adoptee studies is that the assignment process of adoptees to adoptive families is not always random. For example, in case of related adoptions, the genetic matches are obvious. Whereas some studies are able to eliminate cases of genetically related adoption from the data, results of other studies are potentially affected by the presence of genetically related adoptions in the data. Another problem is that placement of children into families in cases of non-related adoptions has not been always random. In fact, for example Björklund et al. (2004) mention that Swedish adoption agencies explicitly made instructions for their personnel that children should be placed into families whose background matches background of biological parents. It is also possible that better educated parents could manage to adopt children from more favourable backgrounds. In cases of international adoptions, the adoptions seem to be more random, since related adoptions are out of the question and the information on children's background is limited: adoptive agencies and parents typically know adoptee's gender, age, and country of origin (Holmlund et al. 2011).

b) Assumption that adoptions take place at birth

The assumption states that children are adopted immediately at birth and thus are able to receive the full impact of adoptive parents' education. This ensures that children receive the full treatment effect of post-birth environment. If this is not the case, some children receive only part of adoptive parent's treatment and the effect of parental schooling would be underestimated. At the same time, this assumption does not necessarily need to hold if regression controls for the age at which child was adopted.

In the reviewed adoption studies, it was not always possible to determine the age at which the child arrived into the family. However, it is rather clear that typically adoptions do not take place immediately after birth, the time lapse between birth and placement to adoptive parents is from several months to several years. It is widely recognized that the first months and years are extremely important for human development, and the fact that children are not receiving parental treatment during this crucial time is a severe problem of adoption studies.

2.4.2. External Validity

The question we address next is whether estimates of intergenerational effect obtained with samples of adoptive parents and children are generalizable to a larger population of representative biological parents and children. In particular, we are interested in the assumptions we must make in order to extrapolate the estimated treatment effect from the family environment on the larger population.

Assumptions needed for external validity of adoption results are necessary in order to interpret the intergenerational estimates using adoptees as representing for the population of all parents and children. According to Björklund et al (2004) and Holmlund et al. (2011), in order to interpret the estimates of α_1 and α_2 in equation (2^0) as a consistent estimate of α_1 and α_2 in equation (2), we need to make four assumptions: identical distribution assumption, assumption of equal treatment, constant effect assumption, and, finally, assumption concerning the functional form of the model of intergenerational transmission of education.

Identical distribution assumption states that the characteristics that make adoptees and their adoptive parents different from any other children and parents are not related to educational outcomes. Assumption of equal treatment states that parents do not treat their own-birth children differently from adopted children would they have been similar in any other way than their genetic link. Constant effect assumption implies that adopted children respond to parental treatment in the same way as own-birth children. Assumption concerning the functional form of the intergenerational transmission model implies that mobility across generations is indeed linear and that Equation 2 correctly represents how education is transmitted.

a) Identical distribution assumption

We have a reasonably clear picture on how the school outcomes of adoptees and their adoptive parents compare to that of other children and parents; that is, they considerably differ (Sacerdote 2007). However, in order to extrapolate the results from adoptive families on the general population we need to assume that parents and children in adoptive and non-adoptive families are similar and comparable to each other. Holmlund et al. (2011) call this assumption “the identical distribution assumption”.

Parents who adopt children might differ from parents who raise their own-birth children is some substantial ways. For example, adoptive parents are typically higher educated than other parents and their income is above median. Thus, the sample of adoptive families does not account for all the home environments that are present in general population: lower SES families are not represented. In addition, adoptive parents may be self-selected to take up the task of raising children or may be selected on some characteristics by adoption agencies. Another possibility is that many of the prospective parents start to think about adopting a child after having experienced fertility problems; it has been shown that fertility falls with the level of education of both the mother and father. Therefore, adoptive parents potentially have several distinct features which make them different from other parents.

It has been also shown that adoptive children differ from children who grow with their biological parents. Adoptees are typically lower educated than other children, probably because of emotional problems that come from the adoption experience or poor biological family background (Björklund et al. 2006 – check this). For example, adoptive children underperform at school and reveal more emotional problems than their classmates (Holmlund et al. 2011). As Björklund et al. (2006) note, if these problems reflect direct causal effect of adoption, other outcomes and schooling among them might also be affected. In general, it can be claimed that adoptive children have on average disadvantaged pre-birth environment and favourable post-birth environment (Björklund et al. 2006).

Even if parents and children in adoptive families differ from general population, it does not necessarily mean that results of studies of schooling of adoptees can not be extrapolated to general population. It would be enough to show in the data that the characteristics that make adoptees and their adoptive parents different from all other children and parents are not related to educational attainment in any way. To sum up, it seems to be widely accepted in adoption literature that adoptive children and adoptive parents differ somehow from other parents and children, but it is unclear whether these differences affect how educational outcomes are transmitted.

b) Constant effect assumption

This assumption states that adoptees respond to parents' treatment in a similar way compared to non-adoptees. It implies that the fact of adoption per se does not alter the strength of intergenerational association among schooling of parents and children. By imposing constant effect assumption we argue that, for example, the time spent at nursery and the fact of adoption per se (the break from the biological mother) does not affect the strength of intergenerational associations in education.

c) Assumption of no differential treatment

This assumption states that the fact that children were adopted and the absence of genetic link to adoptive children does not alter parent's behaviour. This means that parents treat their adoptive children in the same way as if they would treat their own-birth children. Adoption studies often call to the differential (unfavourable comparing to treatment of own-birth children) treatment of adoptees by their adoptive parents as "Cinderella effect". The idea is that adoptive parents, perhaps of some evolutionary reasons, would invest less in their adoptive child compared to biological child.

The key question here is not even whether "Cinderella effect" exists in parent-child relationships in adoptive families, but whether the absence of genetic link alters family dynamics and parent-child relationship in a way which is affects the transmission of educational outcomes.

Several of the reviewed studies test for differential treatment of adoptees by taking advantage the fact that some parents raise both adopted children and their own biological children. The results of such tests are described in chapter 3.3, but the general conclusion is that no evidence of differential treatment was found.

d) Assumption that the functional form of the model is correct

The final assumption related to the external validity of results concerns the functional form of the model (Equations 2 and 2^0). The idea is that in order to consistently estimate the effects of upbringing and genetics on educational attainment, we need to assume that our underlying model is correct. The underlying model (Equation 2 and Equation 20) implies that mobility of education across generations in linear, meaning that genetic endowments and environmental factors enter linearly and additively (meaning that there is no interaction between genes and environment). These statements have been questioned by many researchers. For example, Björklund et al. (2006) and Holmlund et al. (2011) test for non-linearities in intergenerational transmission of education. Thus, they estimate regressions where child's education is a non-liners function of parental education. Other studies (Björklund et al. 2005) explore interactions between genes and environment. Plomin et al. (1988) reviewed literature that studied gene-environment interactions and concluded that there is no evidence of substantial gene-environment interactions that would alter simple linear model of intergenerational transmission. Recent studies seem to agree with this viewpoint (Holmlund et al. 2011).

2.4.3. Casual effects of parental education

Some authors mention that if we make an additional assumption that schooling is unrelated to parenting skills (that Y_{im} and Y_{if} are uncorrelated with f_{im} and f_{if} in equation 2 and 2^0), then we can claim that transmission coefficients of education estimated for adoptees represent the direct causal impact of parental education on child's education (Plug 2004). While majority of researches say that the coefficients represent the effect of family environment not the effect of parental education alone, some authors seem to call the transmission coefficients for adoptees "causal" (Björklund et al. 2004).

The assumption that child-rearing talent and skills are not related to educational attainment is untestable. Plug (2004) notes that we simply do not know the relationship between education and child-rearing talents. Others do not discuss the issue of causality directly.

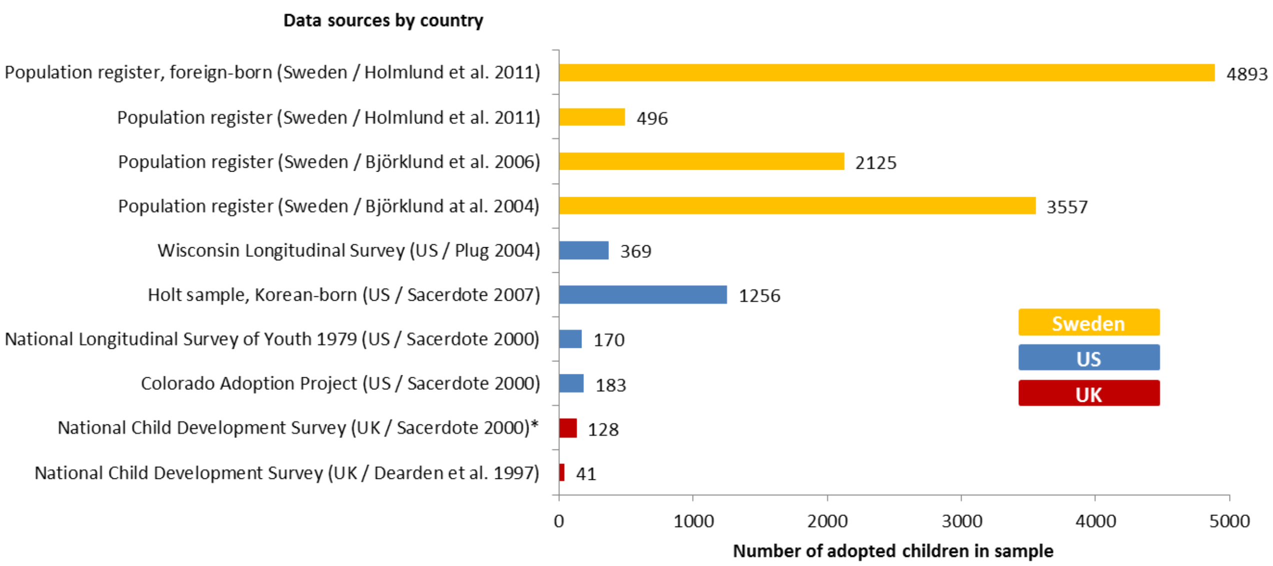
It seems that different authors mean different things by the "causality" of these transmission coefficients. Björklund et al. (2004) call their transmission coefficients causal ("causal effect of education"), but they note that in addition to direct causal effect of education, these coefficients reflect everything else that is correlated with education. Also Holmlund et al. 2011 refer to the transmission coefficients estimated in adoptee studies as "causal". However, just like Björklund et al. 2004, they clarify that transmission coefficient capture the effect of home environment in general, and can not be seen as direct impact of education. According to Plug (2004), even if we wish to say that transmission coefficients represent the causal effect of education, we do not even know whether estimates are biased upwards and downwards. Thus, when it comes to causality, we actually measure the causal effect of family environment, not of parental education and we must interpret the transmission coefficient of education for adoptees as representing combined effect of schooling and everything else related to it.

3. Major findings of adoptee studies

3.1. Reviewed adoptee studies

The most important obstacle to adoptee research has been the scarcity of data on adoptees. There are several studies worldwide that estimate transmission coefficients for adoptees and their adoptive parents. By now, the extensive adoptee studies on the transmission of education have been done in US and Sweden, and one study was done on relatively small set of data from UK. Figure 2 illustrates countries and sizes of adoptee samples used in reviewed studies. There were seven studies reviewed, but since one of the reviewed studies (Holmlund et al. 2011) used two distinct adoptee samples, the Figure 2 shows eight sets of adoptee data. These seven studies were included into the scope of the present work. Samples, methods and results of these studies were analysed and summarized.

Figure 2. Sources of data and size of adoptee samples in reviewed studies



The largest sample (almost 5 000 observations) was used by Holmlund et al. (2011), and consists of foreign-born Swedish adoptees, whose average years of birth is 1979. Paper by Holmlund et al. (2011) compares different identification strategies used to separate environmental influence from genetic influence in educational attainment. In the part of their paper which explores adoptee studies, in addition to foreign-born adoptees, they used data on Swedish-born Swedish adoptees (496 observations). Average year of birth of these children is 1976. Statistics is reported separately for these two groups. Adoptee study comprises only part of the work. The aim of the paper is to test different identification strategies (twins, adoptees, IV) for understanding relative importance of nature and nurture for years of schooling. These strategies are known to be producing differing results, and Holmlund et al. apply all the three strategies to data obtained from the same source and discuss in detail the origins of differences in estimates that these strategies produce. They conclude that the differences between results produced with different identification strategies are because of the different sample used, and not because of the identification methods themselves.

The other Swedish studies (Björklund et al. 2004 and Björklund et al. 2006) also use rather large samples of adoptees, 3557 and 2125 observations. Both studies use data from Swedish population register. The data used on these two studies is very comprehensive and includes information on adoptee’s adoptive as well as biological parents, which makes these studies unique: other adoptee samples do not contain information on biological parents.

Björklund et al. (2004) use the data drawn from Swedish population register. Data contains information on schooling and other outcomes for 7498 adoptees and their parents, children are born on average in 1966. However, only less than half of the observations are used for calculating transmission coefficients of education, because not all adoptees achiever required age at the moment when the study was done. Björklund et al. (2006) use data on 2125 adoptive Swedish children born on average in 1964. They utilize data on both adoptive and biological parents of adoptee to explore what they called “additive effect”. Additive effect is discussed in chapter 3.2.3. “Additive property of transmission coefficients”.

The US data was used in studies by Sacerdote (2000), Sacerdote (2007) and Plug (2004). Sacerdote (2000) studies three data sets. Samples in this study are relatively small, and Sacerdote overcome this problem by including three distinct samples. However, only one of these samples is suitable for calculation of transmission coefficients for education. It is sample which is drawn from the National Longitudinal Survey of Youth 1979. This sample contains 170 adopted children born around 1961.

Sacerdote 2007 uses data on Korean American adoptees from Holt International Children’s Services. Sample is of a solid size and contains 1256 adopted children born on average in 1975. Uniqueness of this sample is that the assignment of children to their adoptive families was quasi random. There was a strict queuing system for couples who wanted to adopt and no matching was made based on child or parents background. In fact, information on children’s family background was very limited.

Plug (2004) obtained data from Wisconsin Longitudinal Survey. Transmission coefficients were calculated for 369 adopted children born on average in 1969.

The UK study was done by Dearden et al. (1997). They use data from National Child Development Survey. The sample is very small: 41 adopted children born in 1958, and all the adoptees in the sample are male.

3.2. Results of reviewed studies

3.2.1. Nurture effect

Estimates of transmission coefficients for years of schooling are presented on Figure 1 and Figure 2 (and in Table 1 in Attachment). The table is taken from Holmlund et al. (2011) with some revisions regarding sample size (Holmlund et al. 2011 report original sample size of the adoptee studies, whereas sample sizes reported in the table are actual samples for which transmission coefficients were estimated). In addition, the table is completed by results reported in Holmlund et al. 2011 study. All the studies reported transmission coefficients for adoptive children (adoptees) and for a comparative sample of children raised by their biological parents (non-adoptees). The reported transmission coefficients are results of regression of child’s years of schooling on parent’s years of schooling. All the studies estimated separate regressions for father’s and mother’s schooling. Separate regression means that schooling of only one parent is included as regressor. Majority of studies (apart from Sacerdote 2007 and Dearden et al. 1997) also reported coefficients for regressions in which schooling of both parents is included (these results are marked in blue color).

Figure 1. Transmission coefficients for non-adoptees (additional years spent by child in school for each additional year of parental education).

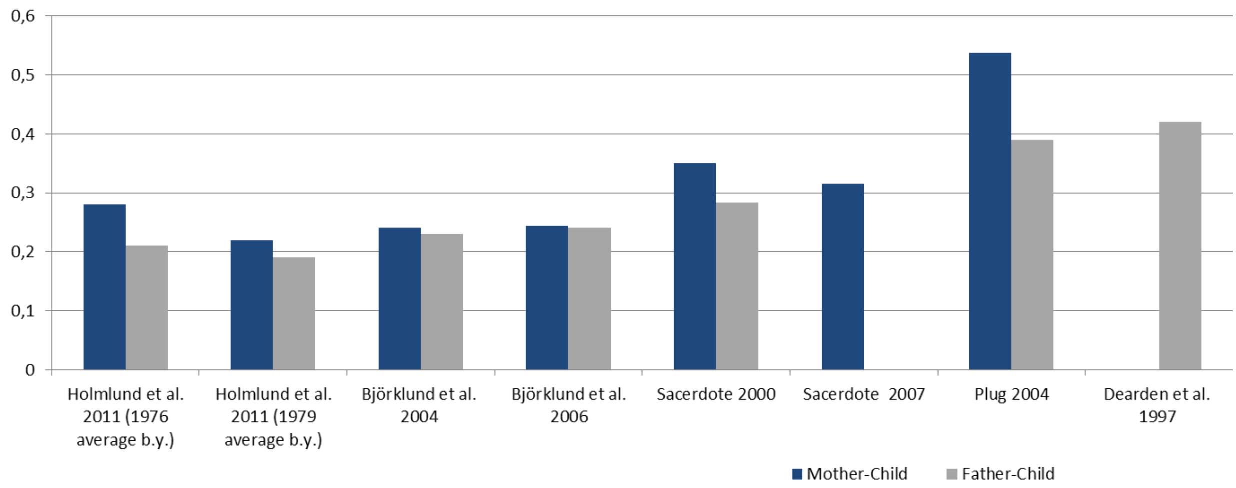
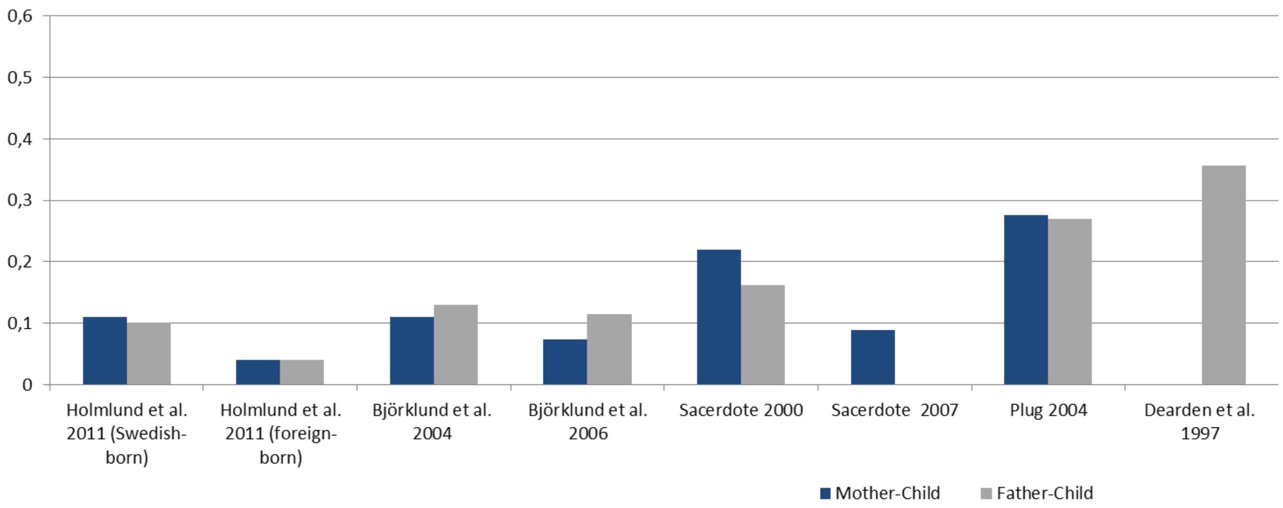


Figure 2. Transmission coefficients for adoptees (additional years spent by child in school for each additional year of parental education).



Plug (2004) obtains the highest estimates of transmission coefficients for non-adoptees and as well as adoptees. He estimates that transmission of years of education for non-adoptees from mother is about 0,54 and from father 0,39. This means that every year of education for mother (for father) is associated with 0,54 (0,39) additional years or around 12 months (4,7 months) of education for child. For adoptees, the estimates of transmission coefficients in their study fall by about a half: transmission coefficient from adoptive mother to adoptive child is 0,28 and from adoptive father to adoptive child is 0,27. If we control for assortative mating by including variables for both parents' schooling into regression, estimated transmission coefficients fall for both mother and father of non-adoptees as well as adoptees. It should be noted that decline in transmission coefficient for father's years of schooling is somewhat less dramatic that decline in transmission coefficient for mother's schooling. This is true for sample of non-adoptees and also for sample of adoptees. Also Dearden et al. (1997) get high estimates for transmission coefficients for both adopted and non-adopted sons and their fathers in comparison to other reviewed studies, but the sample size in their study is very small (only 41 adoptees), and thus no definite conclusions can be made from it.

In studies conducted with the use of Swedish data (Holmlund et al. 2011, Björklund et al. 2004 and Björklund et al. 2006) the full set of transmission coefficients is available: transmission coefficients for separate regressions on child's education on mother's or father's years of schooling, and transmission coefficients estimated in regression which includes schooling of both parents. The transmission coefficients in these studies are similar in magnitude, with transmission coefficients for non-adoptees' parents being in the around 0,2, and coefficient for adoptees' parents about half of that. Consistent with results received by Plug (2004), the coefficients decline in magnitude when education of both parents is included into regression. Transmission coefficients estimated by Holmlund et al. (2011) for foreign-born adoptees' parents stand out from the other results: they are notably smaller (2-3 times smaller) than corresponding estimates obtained in other studies and do ot seem to change significantly with inclusion of both parents education into regression.

Two studies by Bruce Sacerdote estimated transmission coefficients for US adoptees: study made with NLSY79 sample (Sacerdote 2000) and study made with sample of American-Korean adoptees, who were adopted through Holt program (Sacerdote 2007). Transmission coefficients estimated for NLSY79 sample are lower than coefficients estimated another US sample by Plug (2004), but notably higher than coefficients estimated for Swedish samples. As to the estimates based on Holt sample, the coefficient for transmission of mother's years of schooling to adopted children is similar in magnitude to the transmission coefficients found in Swedish studies and transmission coefficients for father's years of schooling are not estimated. The data used by Sacerdote (2007) is publicly available on his website, and this data contain also information on father's schooling. In empirical part of this thesis transmission coefficients for father's years of education are estimated using this publicly available Holt sample data.

Several observations can be made concerning the results on transmission coefficients of years of schooling in the reviewed studies. First of all, estimates for own-birth children indicate that higher parental education is associated with more years of schooling of own children and that, in most cases, the impact of mother's years of schooling is larger than father's. Also transmission coefficients estimated for adoptees are positive and statistically significant. Higher education of adoptive parents is associated with higher education of adoptive children. All the studies found positive and statistically significant schooling effect when mother's and father's education are included as separate regressors. Influence of mother's education seems to be somewhat larger than influence of father's education.

Then, we find that, depending on study, transmission coefficients for adoptees are from 4 to 2 times smaller than coefficients for non-adoptees, depending on study. It suggests that adoptees receive from ¼ to ½ of the transmission effects that non-adoptees receive. Thus, transmission of education to adoptees via nurture is less than half of total transmission to non-adoptees. Next, controlling for assortative mating lowers the estimates of transmission coefficients. When years of schooling of both parents are included into regression, the effect of both parent's education falls, although stays positive. It is interesting that inclusion of spouse's years of schooling has more impact on transmission coefficients estimated for mother's schooling than on transmission coefficients estimated for father's schooling.

It can be noted that estimated magnitude of impact of parental education on adoptee's education is larger in smaller samples than in larger samples. Smaller samples used in Plug (2004), Dearden et al. (1997) and Sacerdote (2000) produce up to two times higher transmission coefficients for adoptees that larger samples used in Sacerdote (2007), Björklund et al (2004 and 2006), and Homlund et al (2011). The coefficients estimated by Björklund et al. (2004), Björklund et al. (2006), Sacerdote (2007) and Holmlund et al. (2011, coefficients for Swedish-born adoptees) are within one standard error from each other. As Sacerdote (2011) suggests, one possible explanation for the finding that transmission coefficients are larger in smaller samples is that the three smaller samples (NLSY, WLS and NCDS) have strong positive selection of adoptees into families in which the healthiest or most naturally able infants were more likely to be adopted by the higher education mothers. In fact, this hypothesis is supported by the fact that smallest transmission coefficients were estimated for samples of foreign-born adoptees (Korean-American adoptees in Sacerdote 2007 and foreign-born Swedish adoptees in Holmlund et al. 2011). In foreign adoptions, matching on child's biological parents' characteristics is much less likely, because information on child's background is limited.

In addition, results vary by country of study: in Swedish samples transmission of education from parents to children is lower than is US samples. However, in both Swedish and US studies transmission coefficients for adoptees are about ¼ to ½ of transmission coefficients to non-adoptees. This means that, if models are correctly specified, estimations of how much family environment contributes to intergenerational transmission of education vary from 25% to 50%. There does not seem to be any significant differences in relative importance of family environment between Swedish and US studies. Transmission of educational attainment (measured is years of schooling) to adoptees via nurture is about half or less than half of transmission to non-adoptees.

3.2.2. Nature effect

In the study by Björklund et al. (2006) also information on education of adoptees' biological parents was available. The study used data on biological parents' education to estimate transmission coefficients of years of schooling for biological parents of adoptees. The analysis shows how much of the transmission remains when biological parents are not participating in upbringing the child.

Figure 3. Transmission coefficients for adoptees from their biological and adoptive parents (additional years spent by child in school for each additional year of parental education).

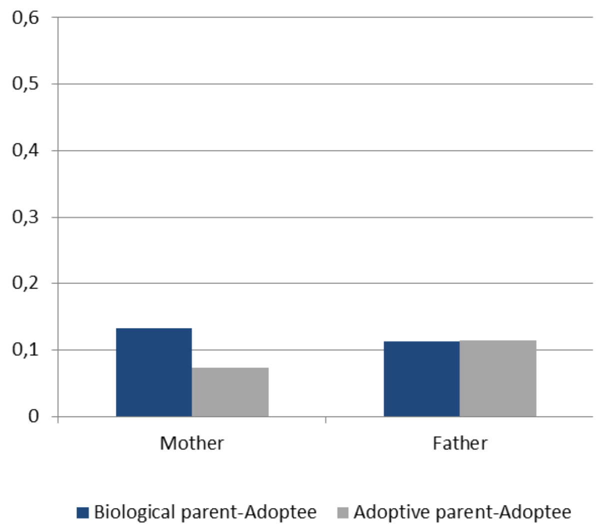


Figure 3 (and Table 2 in the Attachment) summarizes the results from Björklund et al. (2006) regarding transmission coefficients of education. The estimates of transmission coefficients indicate that there is statistically significant (significant at 1% level) positive effect of parents' on schooling their biological child's schooling, even when the parents do not raise the child themselves. The effect of biological parents on adoptees' education is about half of the effect that parents who raise their own biological children have on their kids' education. When both spouses' education is included into regression, the effect of both biological parents on adoptee's education still stays positive and statistically significant (at 1% level). The effect of biological mother seems to be slightly higher than the effect of biological father. However, inclusion of both parents' education simultaneously into regression affects results for adoptive parents: while impact of adoptive father's education stays positive and statistically significant, the maternal effect is no longer significant and close to zero. Björklund et al. (2006) note that these surprising results are in line with other studies on intergenerational transmission of schooling that control for inherited ability and assortative mating. These studies produce schooling effects for fathers that are higher than the schooling effects for mothers (Behrman and Rosenzweig 2002).

Björklund et al. (2006) suggest the transmission coefficient for adoptee's biological mother captures the effect of genetics and pre-natal environment, whereas the transmission coefficient for father's education represents only the effect of genes. The reasoning behind this argument is that in pre-natal stage, mother's lifestyle influences the pre-natal environment for the child, whereas father's participation is limited to transmitting genetic material. We can calculate the impact of prenatal environment by subtracting transmission coefficient for biological father from transmission coefficient for biological mother:

(0,132-0,113) = 0,019 and 0,019 / 0,113 = 17%

This difference is calculated for coefficients obtained by separate regressions of child's schooling on mother's and father's schooling. According to this specification, the magnitude of the impact of prenatal environment is only 17% as high as pure genetic impact. If we use transmission coefficients estimated from regression where both parents' education is included simultaneously, then the relative effect of prenatal environment comparing to genetic effect falls further to 7%:

(0,101-0,094) = 0,007 and 0,007/ 0,094 = 7%

Thus, in transmission of education, the effect attributed to prenatal environment seems to be relatively small.

3.2.3. Additive property of transmission coefficients

The uniqueness if data set used by Björklund et al. (2006) it that availability of comprehensive information on adoptees' biological parents enables estimating the effect of genetically transferred abilities directly. Thus, it becomes possible to estimate both nature and nurture part of that total transmission directly from the data. Björklund et al. (2006) find an interesting feature, which they refer to as "an additive property".

Björklund et al. (2006) estimate intergenerational regression for years of schooling for children raised by their biological parents and they find coefficient estimates 0,158 for the mother and 0,170 for the father. These estimates can be seen as reflecting the effects of nature and nurture. A fascinating part is that the estimate for the mother who raises her biological child is very close to 0,122 (0,101 + 0,021), which is the sum of the estimates for coefficients for the biological and adoptive mothers of an adopted child. Situation with estimates for fathers is very similar: the 1,70 estimate for the father who raises his biological child is very close to 0,188 (0,094 + 0,094), which is the sum of coefficients for the biological and adoptive fathers of an adopted child.

This suggests a possibility that *"almost absurdly simple model of additive pre-birth and post-birth parental effects can account for intergenerational associations in socioeconomic status across a variety of family types"* (Björklund et al. 2006). Björklund et al. (2007) further studied this phenomenon. The used the same Swedish data set used by Björklund et al. (2006) and explored intergenerational associations not only for adoptees and children raised by their biological parents, but also for four other samples where the degree of genetic relatedness between children and parents varies. Thus, their data included other samples in which children were raised by one biological parent with other parent absent at least some of the time, and also samples that represented families where children were raised with or without a stepparent in the family. Findings of Björklund et al. (2007) do not contradict the suggested simple additive model, and they argue that both nature and nurture are of substantial importance.

At the same time, Björklund et al. (2007) indicate that these results are true for a relatively developed and rich society, with well-developed welfare state. Thus, Swedish children were raised in a relatively homogeneous environment, regardless of their family background. Björklund et al. (2007) note that in less developed countries the variety of post-birth environments might lead to a higher importance of nurture. They conclude that similar study made for a less developed country (if the required information could be obtained) would be very enlightening.

3.3. Interpretation of results of reviewed studies

The results of reviewed studies are interpreted in the light of internal and external validity conditions discussed earlier in chapter 2.4 "Interpretation of transmission coefficients in adoptee studies". It was determined for each of the seven reviewed studies whether conditions needed for internal and external validity of study are satisfied.

3.3.1. Causal effect of nurture on adopted children's education

Adoptee studies of transmission of education seek to estimate the causal effect of upbringing (nurture) on educational attainment. Transmission coefficients estimated in intergenerational regressions for years of schooling for adoptees and their adoptive parents can be interpreted as estimates of causal effect of upbringing under two conditions. Firstly, placement of children into adoptive families should be random and, secondly, adoptions should take place at birth. These assumptions necessary for internal validity were discussed in detail in chapter 2.4.1 “Internal validity”. We now examines whether these two conditions hold in the reviewed studies.

a) Random assignment

Only one of the reviewed studies was based on a sample where selective process was effectively random. Sacerdote (2007) uses sample of Korean-American adoptees who were adopted in through Holt program. He shows that the system of adoption applied in Holt project guaranteed random placement: children were assigned to parents strictly on queuing basis and no matching was made. He also demonstrates with the data that characteristics of adoptive and biological parents of children are not related.

The rest of the studies are based on samples where selective placement of possible and was likely to take place, at least to some extent. Björklund et al. (2006) perform tests to find out whether there are statistical evidence of selective placement, but they find no trace of if the data. They conclude that placement of children into families can be regarded as random in their sample.

All the other reviewed studies suffer from the problem of selective placement. In reviewed literature, two strategies seem to be used to deal with this problem. The first strategy is to show that selective placement did not affect the estimated regressions and transmission coefficients of education. The second option is to explicitly control for selective placement. Björklund et al. (2004) test for selective placement and find evidence suggesting that it was a common practise in Sweden in 1960. However, they also show that selective placement did not alter results of their estimates. Holmlund et al. (2011) find evidence of selective placement in data on foreign-born adoptees: they show that more educated parents adopted younger children and children from more economically developed countries. For Swedish-born adoptees, they find that matching was made based on birth mother’s and adoptive parents’ background. To control for it, they include into regression age and schooling of birth mother. It is interesting that inclusion of these control variables does not affect estimated coefficients.

Sacerdote 2000, Plug 2004 and Dearden et al. 1997 are all likely to have selective placement of adoptees in their samples. Sacerdote (2002) admits that there could be selective placement in data used in Sacerdote (2000). He tests for matching based on socioeconomic status, and finds that socioeconomic status of birth mother and adoptive family are uncorrelated. However, selection could have been made based on other criteria, such as adoptee health or weight. Plug (2004) notes that his sample (WLS sample) contains relative adoptions. In overall, it is very likely that selective placement was present in these data, and that it might have caused higher estimates for intergenerational transmission of education in these studies.

The adoption strategy to identify causal effect of nurture exploits the idea that adoptees do not share their adoptive parents' genes and their backgrounds are non-related. However, this condition does not seem to hold in most of the reviewed studies: assignment of children into families was actually non-random, with the exception of Sacerdote (2007) study of American-Korean adoptees.

b) Adoptions take place at birth

In order for adoptees to receive the full theoretical impact of parent's education, they need to be laced into adoptive families immediately after birth. However, this was not the case in the samples used in reviewed studied. One study was done with a sample where children were adopted during their first year of life: Holmlund et al. (2011) have information on age of adoption and they limit sample of foreign-born adoptees to those children who were adopted at 6 months of age as the latest.

In study by (Sacerdote), age of adoption varies between under 1 year of age and 4 years of age. However, the age of adoption is not controlled for in estimated intergenerational regressions for education. Information on adoption age was also available for the samples used in Björklund et al. (2004) and Björklund et al. (2006). Like Sacerdote (2007), they do not include control for adoption age into regression, but they separately show that the age of adoption does not seriously affect estimates for transmission coefficients of education. The other studies (Plug 2004, Dearden et al. 1997) do not have information on age of adoption.

In short, in the reviewed studies children are not adopted at birth. The adoption age varies between 3 months to 2-3 years, depending on sample. Dummies for adoption age are included only in study by Sacerdote (2007).

3.3.2. Causal effect of nurture on education in general population

Next we discuss whether the results obtained for adopted children and their parents can be extrapolated on general population. Four conditions that were discussed in chapter 2.4.2 "External validity" need to be met in order to claim that the effect of parental education and nurture component in general is the same for adoptive children and for children raise by their biological parents. In order to make general conclusions about the effect of nurture on children's education in general population (where majority is raised by their own-birth parents), it was checked whether the four necessary conditions hold in the reviewed adoptee studies.

a) Identical distribution

According to condition of identical distribution, adoptive parents and adoptive children should be no different from other parents in children in respects that are related to transmission of education. This condition is thoroughly discussed in Björklund et al. (2004) and Björklund et al. (2006). As Björklund et al. (2004) note, we might expect that adoptive parents have better parenting skills than on population of parents in average. Thus, adoptive parents first select themselves by making decision to adopt and those expressing a strong preference for parenthood. Then, they are also selected by adoptive agencies as prospective suitable parents. Björklund et al. (2004) test whether adoptive parents have better parenting skills that are related to schooling outcome of children that they raise. They focus on parents that raise both adopted and own-birth children and show that adoptive parents do not have better parenting skills in ways that are related to effects of their education and home environment on child's educational outcome. Also Plug (2004) explores this issues (for mothers only) and finds that adoptive mothers are not significantly different from mothers who raise only their own-birth children in terms of what effect their education has on education of own-birth children. Björklund et al. (2006) study the same matter and find that parents who have both own-birth and adopted children have higher transmission coefficient of education to their own-birth children. As the authors note, this result indicates possible Cinderella effect (Cinderella effect was discussed in chapter 2.4.2 "External validity"). However, at the same time Björklund et al. (2006) find that adoptees who have siblings that are own-birth children of adoptive parents do not receive less effect of transmission of education comparing to adoptees that do not have such siblings. It seems that these two findings combined might indicate that adoptive parents in this given dataset in fact have better parenting skills.

Björklund et al. (2004) also discuss whether adopted children differ from non-adopted children in a way that is related to intergenerational transmission of education. According to them, we might expect that adoptees have disadvantaged background, perhaps because of having inferior genes, or because of negative early environmental experiences during pre-natal time or during institutional caretaking. Björklund et al. (2004) test impact of these unobservables on a group of own-birth children with full siblings that are adopted out. Indeed, it is reasonable to assume that, apart from the institutional care experience, this group of children shares similar background with adoptees. Björklund et al. (2004) conclude that adoptive children do not differ from other children in ways related to transmission of schooling. Similar results are obtained by Björklund et al. (2006). As they note, samples of adoptees and own-birth children are hardly comparable: adoptees come from less-advantage pre-birth environment, but are raise in favourable port-birth environment. We do not find similar cases in the population of own-birth children. To tests whether intergenerational transmission of education to adoptees differs from intergenerational transmission of education to own-birth children, Björklund et al. (2006) compare adoptee sample to a sample of children who are born and raised in less-advantaged environment and to a sample of children who are born and raised in a favorable environment. They find that there are no significant differences in respect of how parental education impacts child's education between adoptees and non-adoptees from those two samples.

Holmlund et al. (2011) in their discussion of regression results state the fact that children and parents are different in adoptive families. They do not run any additional test to study presence or absence of possible differences related to transmission of education. In case of foreign adoptions, like Korean-American adoptees in Holt sample (Sacerdote 2007), the adoptees are, for example, physically different looking than majority of American children. However, it is unclear whether this is relevant for intergenerational transmission of education. In overall, the question whether adoptive parents and children are comparable to parents and to other parents and children seems to be hard to answer.

b) Constant effect

Constant effect condition requires that, when it comes to transmission of education, adoptees should respond to parental treatment in the same way as own-birth children. As Holmlund et al. (2011) note, *"the adoption literature has put forward various heterogeneity mechanisms to explain why adopted children may respond differently to the same impact of a one-year change in parental schooling"*. For example, it has been shown that adopted children are more likely than own-birth children to suffer from emotional problems and perhaps these emotional problems might affect how perceptive the adoptees are to their parents' treatment (Holmlund et al. 2011).

However, Björklund et al. (2006) argue that their finding that total impact of biological and adoptive parents is similar in magnitude to impact of parents who raise their own children (discussed in chapter 3.2.3. "Additive property of transmission coefficients") demonstrates that adoptees are as perceptive to parental influence as own-birth children are. Holmlund et al. (2011) also use the additive property found by Björklund et al. (2006) to argue that there are no reasons to believe that the effect of parental educations on adoptees would differ from own-birth children. Other authors of reviewed adoptee studies do not discuss this matter. Therefore, it can be summed up that current adoption literature seems to agree that the constant effect assumption can be regarded as a reasonable one.

c) Differential treatment

The studies of Swedish samples (Holmlund et al. 2011, Björklund et al. 2002, Björklund et al. 2006) discuss whether parents treat their own-birth and adoptive children differently and, if there are treatment differentials, then how they might affect the intergenerational transmission of education. Swedish studies and Plug (2004) run tests on their data and conclude that there is no evidence of differential treatment effect among adoptees and own-birth children. For example, one of concerns is that there might be the Cinderella effect, which implies that parents invest less in their adoptive children than in own-birth children. This can be tested by comparing intergenerational transmission coefficients for adoptees who have siblings that are own-birth children to the parents in the family to adoptees whose siblings were also adopted. Björklund et al. (2004) and Plug (2004) run this test, and find no difference in the magnitude of transmission coefficients for these two groups of adoptees. Thus, they conclude that there is no evidence of differential treatment in their data.

On the other hand, as Holmlund et al. (2011) note, "*differences in upbringing may also lead to larger parental schooling effects if parents are instructed to be more patient and tolerant toward their adopted children"*. They mention that some of the textbooks for adoptive parents explicitly instruct parents to be more unprejudiced and encouraging towards their adoptive children. In addition, parents might choose to invest more in their less talented children out of compensatory motives. However, no evidence of such motives were found in the reviewed studies.

To sum up, the adoptee literature seems to agree that the generality of estimates made on adoptee samples is not sensitive to this particular problem.

d) Functional form

The condition deals with the specification of model for intergenerational transmission of education. In particular, the transmission model is linear, meaning that is assumes that the magnitude of impact of education of parents does not depend on their educational level. However, it was shown that intergenerational transmissions are stronger at the top than at the bottom of schooling distribution (Björklund et al. 2006). This is also true for income transmissions. Much stronger transmission effects for children of more educated parents were also found in earlier mobility studies (Behrman and Taubman 1990; Solon 1992; Björklund and Chadwick 2003).

Understanding why intergenerational transmissions are much stronger at the top than in the bottom of the educational and income distribution would be very illuminating. Some authors have argued that this is caused by interactions between nature and nurture (Dickens and Flynn 2001, Ridley 2003). The argument is that if smart children would benefit relatively more from having highly educated parents, the intergenerational transmission would be greatest among highly educated and high-income families. Proving this hypothesis, however, is very difficult (Björklund et al. 2006). The specified intergenerational transmission model does not allow for any interactions between nature and nurture: genes and environment enter into the equation additively. In fact, Björklund et al. (2006) test whether interactive effect of genes and environment can be found in their adoptee sample. To estimate that part of the transmission that comes from the interaction between the postbirth environment (adoptive parents) and genetic factors (biological parents), they include the interacted effect between the adoptive and biological parents. They find positive interaction for mother’s education and father’s earnings, but not for father’s education. Björklund et al. (2006) conclude that non-linear model that also allows for interactions between nature and nurture fits the data best. However, Holmlund et al. (2011) review the previous studies of adoptees. They argue that estimates for interactions of nature and nurture and for nonlinear transmission obtained by Björklund et al. (2006) are too small and that there is not enough evidence to reject the simple linear model. It can be concluded that at the moment there is not enough studies in adoption literature to say support or reject the simple linear model of transmission of education. At the moment, this model seems to be solid enough in explaining intergenerational associations.

4. Empirical study

4.1. Objective of empirical study

The purpose of the empirical part is to estimate the relative importance of nurture in intergenerational transmission of education. I replicate and complete the results of Sacerdote (2007) study which are related to intergenerational transmission of education. The sample which Sacerdote used is publicly available on his webpage3. Sacerdote (2007) estimated the impact of adoptive mother's education on adoptee's education. However, the sample also contains information on adoptive fathers of these adoptees, but results for fathers were not reported in that study. I am not aware of any other study which would use the data about father's education for this particular sample and would estimate intergenerational transmission coefficients. Thus, my aim is to replicate Sacerdote's results for adoptive mothers and complete the analysis of Holt sample by estimating the effect of adoptive father's education on adoptees' education using OLS regressions. I also check whether controlling for assortative mating changes the results by estimating intergenerational regression where both adoptive parents' education is included simultaneously.

4.2. Data used in empirical study

The sample consists of children who were adopted from Korean into American families through the Holt project. The data was collected by Holt organization and Bruce Sacerdote from Holt records and by a mail survey in 2004. The mail survey was targeted to parents and asked them information about their and their children's schooling, income, health and some other basic demographic characteristics. Children who were not adopted through Holt's Korea program and children with special needs were dropped out from the sample. Sacerdote also limited the sample to children who were 19-40 at the moment of the survey. Since Sacerdote estimated results for variety of outcomes, whereas I was interested in educational outcomes only, I have further limited the sample to the children who were 25-40 at the moment of the survey. Parents did not have possibility to choose gender or any other characteristics of their future adoptee. Exception was however made for families with all boys or all girls, who could request a child of opposite gender.

[3] "Public Use Data Set of Adoptees", accessed at: http://www.dartmouth.edu/~bsacerdo/

There are 1256 adoptive children and 1056 own-birth children in the original sample. However, since in my analysis I restricted the sample to the children who were 25-40 at the moment of the survey, the sample size decreased. Exhibit 1 presents the summary statistics for children and parents in the sample.

Exhibit 1. Summary statistics

Variable	Adoptees					Non-adoptees				
	Obs.	Mean	St. Dev.	Min	Max	Obs.	Mean	St. Dev.	Min	Max
Child's current age*	1235	30.15	2.96	25	40	1040	33.31	4.13	25	40
Child is male	1235	0.27	0.45	0	1	1040	0.63	0.48	0	1
Child's age at arrival to US	1235	1.33	0.79	1	5	n.a.	n.a.	n.a.	n.a.	n.a.
Child's years of education	1235	15.09	2.15	9	21	1040	15.92	2.27	9	21
Mother's years of education	1221	15.04	2.48	9	20	1034	15.26	2.44	9	20
Father's years of education	1209	15.91	2.92	9	20	1026	16.31	2.78	9	20

* Childs' age in 2004, when the data was collected.

There are 1235 adoptive children and 1040 own-birth children. Adoptive children are 30 years old on average at the moment of the survey, and own-birth children are on average 33 years old. The majority of adoptees in the sample are females (73%), whereas for the own-birth children the 63% are male. Adoptees' age at the moment of arrival to US and adoption into American families was between 1 and 5 years old, with average adoption age being 1.3 years old. Adoptive children have on average 15.1 years of education, comparing to 15.9 years of education for own-birth children. On average, mothers of adoptees and non-adoptees have respectively 15.0 and 15.3 years of education, and father have 15.9 and 16.3 years of education.

Thus, comparison of adoptee sample to the sample of own-birth children reveals that, firstly, samples of adoptees and non-adoptees are roughly similar in size. Secondly, adoptees are about three years younger that non-adoptees. And, thirdly, own-birth children seem to have slightly more years of education on average.

4.3. Methodology of the empirical study

In the empirical study, I estimate the intergenerational transmission coefficients for adoptive and own-birth children using OLS regression. I regress the years of schooling of adopted children on the years of schooling of their adoptive parents and the years of schooling of own-birth children on years of schooling of their mother and father. Child's gender and age is controlled for. In addition, I control for the year of arrival to US (cohort), as there might be some systematic differences between children who are given up for adoptions in different years. The control for cohort is introduced in case parent and child characteristics co-vary systematically over time (Sacerdote 2007). These specifications correspond to specification made in Sacerdote (2007).

The intergenerational regression of child's years of education on mother's or father's years of education is as following:

$$E_i = \alpha + \beta E_{Pi} + \lambda Male_i + \gamma A_i + \rho C_i + \varepsilon_{i,}$$

where E_i is child's years of education, E_{Pi} is parent's (father's or mother's) years of education, $Male_i$ is dummy for child's gender, A_i full set of single years of age dummies, C_i full set of cohort dummies (year of arrival to US, applicable to adoptees only). The dummy variable for child's gender was specified as 1 for child being male and 0 for child being female. Like in Sacerdote (2007), the regressions also include clustering at family level. Clustering at family level means that if one family had adopted two children, it is counted only once in regression results.

Sacerdote (2007) published the results for mothers', but I also include the results for fathers'. Moreover, I also estimate intergenerational regression which controls for assortative mating by including simultaneously education of both mother and father into regression as explanatory variables:

$$E_i = \alpha + \beta^m E_{Mi} + \beta^f E_{Fi} + \lambda Male_i + \gamma A_i + \rho C_i + \varepsilon_{i,}$$

where E_{Mi} and E_{Fi} are mother's and father's years of education, and other variables are as in the regression equation above.

4.4. Analysis and results of the empirical study

The results of regressions of child's years on education on parents' years of education are presented in Exhibit 2 (as well as Stata outputs for regressions of years of education for adoptees in Attachment, Tables 3-5). The transmission coefficient for adoptive mother is 0.074, significant at 5% significance level. This result is slightly below the estimate obtained in Sacerdote (2007), which was 0.089, but still confidently within one standard deviation from Sacerdote's result. Inclusion of father's years of education into regression does not alter the result substantially. In fact, the estimated transmission coefficient for mother's education slightly increases when father's years of education are included into the regression, and the estimate is still significant at 5% level. On the other hand, there is no evidence that the impact of adoptive father's years of education on adoptive child's years of education is different from zero: the estimated coefficient is positive (0.020), but the p-value of 0.4 (not shown in the Exhibit 2) suggests that the result is not significant. In the simultaneous regression, where education of both parents is included, the coefficient for father's years of education is in fact negative (-0.013), but again the p-value of 0.7 (not shown in the Exhibit 2) means that this result is not significant in statistical sense. Therefore, there is no empirical evidence to conclude that adoptive father's years of education affect adoptees years of education in this sample.

Exhibit 2. Results of OLS regression of child's years of education on parents' years of education

Regressor	**Adoptees**		**Non-adoptees**	
	Obs.	Transmission coefficient	Obs.	Transmission coefficient
Mother's years of education	1023	0.078 (0.029)a*	1034	0.298 (0.032)a**
Father's years of education	1010	0.028 (0.026)a	1026	0.303 (0.027)a**
Mother's years of education (control for assortative mating)	*1003*	*0.077 (0.032)a**	*1025*	*0.165 (0.036)a***
Father's years of education (control for assortative mating)	*1003*	*-0.005 (0.028)a*	*1025*	*0.229 (0.032)a***

*indicates significance at 5 percent level, and ** 1 percent level

Blue italics: control for assortative mating

The transmission coefficient estimated for mother's of non-adoptees is consistent with the estimate published in Sacerdote (2007). Sacerdote (2007) estimated transmission coefficient of 0.315 for biological mother's education who raises her own child, and my estimate is 0.298, which is within one standard deviation from Sacerdote's estimate. My result is significant at 1% significance level. I also find similar effect of biological father's education on own-birth and own-raised child: the transmission coefficient is 0.303 and it is significant at 1% level. The inclusion of both parents education into regression reduces the effect of both parent's education, which is well expected. However, the effect of both parents education stays positive and significant at 1% level. It should be noted that with the inclusion of spouse's education, the effect of mother's education decreases somewhat more relative to the decrease in the effect of father's education. This result is consistent with the previous studies discussed in chapter 3.

To conclude, my estimates are similar to Sacerdote's (2007) estimates for the transmission of years of schooling for mother raising her biological child and mother raising an adoptive child. I also estimate the transmission of education from fathers to adoptive and their biological children. The transmission of education from father to his biological children whom he also raises seems to be similar in magnitude to the transmission of education from mother to her biological children whom she also raises. However, I do not find evidence that adoptive father's education has any impact on education of his adoptive children in the studied Holt sample. I also find that these results are robust to inclusion of both parent's education simultaneously as explanative variables into the regression.

5. Discussion

5.1. Causality in adoptee studies

It is clear that parental education predicts children’s education in a narrow statistical way. However, the fact that more educated parents have more educated children does not mean that schooling causes offsprings' schooling to increase. The question of whether schooling-schooling relationship is causal can help to uncover how education production function works. Sacerdote (2007, 2011) refers to Rubin’s causal model (Rubin 1974). According to Sacerdote, this model provides an useful framework for understanding what is meant by “causal effect” or “treatment effect”. Thus, according to Rubin (and many empirical economists), in order to measure a causal effect there needs to be an identifiable intervention that could be implemented or not implemented. In analogy with the definition for causal relationship between parental earnings and child’s earnings defined in Angrist and Pischke (2009), the causal connection between parental schooling and children's schooling can be defined as the functional relationship that describes how many years a given child would study if his/her parents have obtained less education. In this setup, we might think of schooling decisions of parents as being made in circumstances when the decision maker can realistically go one way or another, even if certain choices are more likely than others. Thus, the causal relationships between child's schooling and schooling of parents tells us how many years child would stay at school if we could either change parental schooling in a perfectly controlled environment, leaving all the other characteristics of the parents unchanged. However, it seems likely that those who went to college would have children who go to college anyway. If so, there is positive selection bias in those who go to college and the regression results exaggerate the benefits of parental college attendance on their children's educational outcomes. The regression coefficients can be interpreted as causal assuming that all other covariates (variables that correlate with the regressor of interest) are known, observed and included into regression (Angrist and Pischke (2009)). This would effectively mean that there are no omitted variables in such a regression.

However, in the reviewed studies parental ability is an omitted variable. We do not know how parental ability relates to parental education. If there is no correlation at all between parental ability and education, our estimates of effect of parental education on child education are causal. If there is a positive correlation between parental ability and education, then our estimate of causal effect of parental education are biased upwards. And, finally, if there is a negative correlation between parental ability and education, then the estimates of causal effect of parental education on child education are biased downwards.

The problem with interpreting estimated transmission coefficient as causal is that education is probably correlated with unobserved parental ability and parental skills. Thus, as Björklund et al. (2006) and Sacerote (2007) note when discussing the results of their intergenerational regressions, transmission coefficients cannot be interpreted as causal due to unobservables and correlations between the regressors. However, currently we are not able to control for these unobservables. Since we do not know the nature of relationship between the parental ability and parental education, it seems reasonable to conclude that the transmission coefficients for adoptees represent the causal effect of family environment on adoptees and not the causal effect of parental education. The family environment in this case is described by parental level of education (and everything that is associated with it). The result might be interesting for adoption agencies, who try to determine the best adoption strategies.

5.2. Key considerations

The studies of adoptees encounter several challenges. Scarcity of data available, small sample size, multicollinearity in regressions, and measurement errors pose restrictions on amount of research in the area and usability of the results of such research.

Thus, there is not much data on adoptees available to start with, as only a very small proportion of children live with adoptive parents, and the samples that were used in studies are rather small. The intergenerational regressions which include education of both parents simultaneously suffer from multicollinearity issues because of assortative mating on the marriage market. Then, measurement error is always an issue for data gathered through survey, as data on education of adoptees and members of their families usually is.

Different studies make different choices regarding the specifications of intergenerational regressions. As Holmlund et al. (2011) note, almost all studies use OLS method and regress educational outcomes of children on educational outcomes of parent, mostly measured by years of schooling. However, there is variation in the choice of control variables in the model. In particular, some studies include spousal education as additional explanatory variable or as a control variable, whereas others do not.

It is not a priori clear whether spousal education should be included as an additional variable. Without the inclusion of spouses' education, the effect of parental schooling represent the both the direct transfer from the given parent and also indirect transfer from the other parent, and thus can be seen as the impact that education of parents has on child's education. When the spouse's schooling is included, the estimated transmission represents the effect of an increase in one parent's schooling on the schooling of the child, net of assortative mating effect. However, meaningful interpretation of the schooling coefficients for father and mother separately is challenging because of the strong collinearity between parental schooling (Holmlund et al. 2011).

Oreopoulos et al. (2006) proposed a strategy for overcoming the collinearity issue: they suggest using the sum of mother's and father's schooling as the regressor of interest in intergenerational regression. In such a setup, the coefficient of interest shows the impact of one additional year of mother's or father's schooling on child's schooling. Assuming that mother's and father's schooling affect child's schooling equally, this regression corresponds to the regression model where education of both parents is included. Intergenerational regression specified in this way controls for assortative mating, avoids multicollinearity and produces more precise estimates for transmission coefficients (Holmlund et al. 2011).

The choice of regressors depends on what questions are being answered. If we are interested in the final outcome for children's schooling, then we can estimate separate regressions for father's and mother's schooling, because it does not matter through which mechanisms (with assortative mating being one of them) the schooling is passed to children. However, if we study the effect of raising father's or mother's education, then we need to take the assortative mating into account and include simultaneously schooling of both mother and father. And, finally, if we assume that effects of both parents' education are equal, we can take gain more statistical precision by regressing child's schooling on sum of parental schooling. At the same time, we do not capture possible effects that are conditional upon parent's gender (Holmlund et al. 2011).

The reviewed studies indicate that the partial effects of both parents' schooling fall when spouse's education is included as an additional regressor (Sacerdote 2000, Plug 2004, Björklund et al. 2004, Björklund et al. 2006, Holmlund et al. 2011). Moreover, the studies indicate that when father's education is controlled for, the effect of mother's education on child education drops dramatically: when father's education is included in the same regression, mother's education loses significance or approaches zero. At the same time, the effect of father's education remains positive and significant when mother's education is included in the same regression. The impact that inclusion of father's education has on coefficient of mother's education is surprising. These results are in apparent contradiction with widely held wisdom that mother's schooling is important for her child's schooling, and that mother's schooling is more important than the schooling of her husband.

Plug (2004), Björklund et al. (2006) and Holmlund et al. (2011) regress years of education on sum of mother's and father's years of education. They receive results for transmission coefficients that lie between the transmission coefficients found in regressions with separate and simultaneous inclusion of parental education. This results is not surprising, as the regressions which do not control for assortative mating are likely to overestimate the individual effect of mother's and father's education, whereas regressions where education of both parents is included simultaneously might result in too low transmission coefficients (Holmlund et al. 2011).

In my estimates made on Holt sample data, the effect of mother's education on own-birth child's education falls from 0,3 to 0,165 when father's education is included, whereas the effect of father's education on own-birth child's education falls from 0,303 to 0,229 when mother's education is included. In the case of adoptive children, the effect of mother's education does not change much when father's education is included, from 0,078 to 0,077, whereas the effect of father's education is insignificant both with and without inclusion of mother's education. This coefficient is similar to the corresponding results found by Holmlund et al. (2011) for foreign-born adoptees.

What is the influence of other characteristics of parents and family on children's education? For example, it has been claimed that at least some of the transmission effect of education works through family income. In order to examine how various family characteristics and attributes affect children's outcomes, a multiple regression approach was used by some authors in addition to estimating regressions for intergenerational transmission of outcomes. Plug and Vijverberg (2003) and Sacerdote (2007) regress child's outcome on a number of family characteristics, such as parental schooling, family income and family size. This allows measuring directly what family characteristics have the largest and most statistically significant influences on adoptee's outcomes. Sacerdote (2007) estimates the effect of family size on adoptee's educational outcomes by including mother's education and family size into the same regression model. He finds that the number of children in the family is a statistically significant predictor of adoptee's educational attainment. While his study shows that each additional year of mother's education is associated with 0,09 additional year of education for adoptee, the effect of each additional child in the family is a decrease in adoptee's years of education by 0,12 years (Sacerdote 2011). Thus, the magnitude of the effect of number of children in the family is statistically comparable to the magnitude of the effect of parental education on children's education. There are at least two interpretations for these results:

either number of children is correlated with some other unobservable family characteristics that affect children's education, or the number of children influences children's education directly through, for example, decreased maternal attention received by each child.

Just as in the case on intergenerational regressions for education, we cannot take the regression coefficients estimated with multiple regressions as causal due to number of reasons, such as for example measurement errors, endogenous relationships among variables and unobservables, but they provide a starting point for understanding how the human capital is formed and what parental inputs matter most even in the absence of genetic link between parents and children (Sacerdote 2011). Multiple regressions are also important for better understanding the transmission coefficients of education discussed in this study. Thus, if transmission of education from parents to children partly operates through income, then the estimated transmission coefficients for education also include the effect of income.

The importance of family income for children's education has been studied thoroughly in the literature on economics of education and adoptee studies. For example, Sacerdote (2007) estimates the effect of parental income using Holt sample data and finds little evidence for a direct effect of parental income on adoptee's income and education, controlling for other family characteristics. Also Plug (2004) checks for the effect of inclusion of income into the regression for transmission of education and finds that inclusion of income does not significantly alter the results. These findings are consistent with the work of Mayer (1997) and Blau (1999), who find that the family income per se does not influence children's education attainment.

6. Other identification strategies

In addition to transmission coefficients, two other strategies have been used to study the heritability of schooling. The first strategy is the variance decomposition approach, also known as behavioural genetics (BG) modelling. The second strategy relies on use of instrumental variables (IV), such as educational reforms that were implemented in gradually in different parts of the country.

6.1. Behavioral genetics

BG models are applied to separate impacts of genetics and environment on various outcomes in population. BG model uses differences in degrees of genetic relatedness among relatives to infer the role of genes and environment for certain outcomes. The majority of BG studies use twin data, but also studies of adoptees became more common as availability of data on adoptees improved.

BG modelling has been widely used in health sciences, psychology and sociological researches, and it has also been applied by economists to study nature and nurture of educational outcomes. Behavioral genetics has been used to estimate heritability of variety of children’s outcomes, such as health status, different personality traits and life choices. In social science, IQ (Intelligence Quotient) is arguably the most popular outcome studied within BG framework. These studies have estimated that for adult IQ, genetic factors explain about 50 to 60% of the variation in final outcome at adult age (Devlin, et al. (1994), while family environment explains only a small portion of total variation. This result is very robust across studies. Somewhat higher effect of family environment was found for younger adoptees, but still it was three times smaller in magnitude than the effect of genetics (Cardon and Cherny 1994). It has also been shown that the effect of family environment on different outcomes, including IQ, tends to diminish in adulthood and even further declines in older age (Plomin et al. 2001).

The existing BG studies of determinants of educational attainment with the twins strategy are the study Behrman and Taubman (1977) and Behrman and Taubman (1989). Consistent with twin studies of IQ that find high heritability, Behrman and Taubman find that genetic effects explain up to 88% of the variation in schooling, and family environment explains little or none of the variance in schooling. As to BG studies using adoptee data, there are three major studies that decompose variance in years of education for adoptees. The first study was made by Teasdale and Owen (1984). They apply BG model to 163 pairs of adoptees in Denmark and find that family environment explains only 5% of the variation in years of education, and 68% of the variation is explained by genetics. Later study by Scarr and Weinberg (1994) uses data on 59 adoptive siblings and 105 nonadoptive siblings in Minnesota whose age is between 22 and 30. They find that family environment explains 13% of the variation in years of education, whereas genetic factors explain 38%, and about 50% of the variance is left unexplained. More than ten years later, Sacerdote (2007) decomposes the variance of educational achievements for Korean American adoptees and American nonadoptees, and finds results that are very much mirroring the results of study of Minnesota adoptees. Around 16% of the variance seems to be attributed to family environment, 41% is attributed to genetic factors and 46% is unexplained. Unlike previous studies, the sample used by Sacerdote (2007) has rather solid sample of 1650 adoptees and 1196 non-adoptees.

So far, BG adoptee studies which decompose years of schooling seem to obtain results that are similar to the results of much larger pool of research on decomposition of IQ. The results suggest that nature seems to play a large role, while the effect of family environment is very small indeed.

Many authors, including Ridley (2003) and Sacerdote (2007) have argued that interactions between genes and environment or the endogeneity of environment will cause the BG model to understate the importance of shared environment and overstate the importance of genetic factors. In particular, Turkheimer et al. (2003) find that measured heritability of IQ is lower for children who grow up in less advantaged environment. Lizzeri and Siniscalchi (2007) point out that if parental expectations are lower for adoptive children than for their own-birth children, learning process for adoptees and non-adoptees will likely differ and that this can lead BG estimates to overstate heritability. As Scarr and Weinberg (1983) note, the question does not necessarily need to be stated as “nature *or* nurture”; genes need the right environment to express themselves.

The simple BG model can be extended to include wider circle of relatives, for example parents, grandparents and cousins. This general model is known as Fisher’s Polygenetic Model (Behrman and Taubman, 1989). The model can be further complicated through easing the assumption of no relationship between genes and environment by explicitly modelling gene-environment correlations in the equations (Goldberg, 1979). Furthermore, one could also study the patterns of correlations among siblings (and parent-child pairs) with not only varying degrees of genetic relatedness, but also with varying time of co-residence during childhood to estimate the role of genes and of shared and unshared environmental influences (Falconer 1981 in Duncan 2001).

Although BG methods have their limitations and interpretation of results is often tricky, the underlying question of relative nature-nurture importance is very intriguing. Furthermore, from the practical point of view economists are not even interested in the true decomposition of educational attainment on nature and nurture components. The real issues of interest are possibilities of interventions and their cost-effectiveness. Making reference to Goldberger's (1979) example of the benefits of eyeglasses, if we could find the type of intervention which gives the best results, it does not matter whether the source of original variation in outcomes originates in genetics or in certain aspects of family environment. To take Goldberger's (1979) example, a finding that most part of the variation in the eyesight is heritable genetically, however, this effect has been successfully muted by the invention and use of eyeglasses. The use of eyeglasses adds great utility to people and is cost-effective, thus correcting the outcome which is largely pre-determined genetically. Summing up, finding out what fraction of the existing variance is environmental does inform us about effects that certain interventions might have on the final result. Currently the research has shifted from BG modelling to other strategies, mainly various types of regressions (Sacerdote 2011).

6.2. Instrumental variables studies

Instrumental variable studies use the change in compulsory schooling laws that are introduced in different country municipalities at different times. When the compulsory years of schooling increase at different municipalities at different times, the result is that some parents experience the extra years of schooling, whereas other do not, and these groups of parents are otherwise similar to each other on any other point but their year and municipality of birth. For example, Black et al. (2005) use differences in compulsory schooling laws that were made in Norway during 1960s and early 1970s in different municipalities at different times. Compulsory schooling increased by two years (from seven to nine years), resulting in some parents having two more years of schooling than other parents, depending on the region and year when they were born. Thus, the reform generated exogenous variation in parental schooling that does not depend on other endowments of these parents. With the timing of reform used as an instrument for parental schooling, Black et al. (2005) arrive at estimates that are statistically insignificant and imprecise. However, when they restrict the sample only to the parent who have nine years of education at maximum, assuming that the reform has most influence on those who acquire only the minimum compulsory years of education, they find small but positive effect for mother's schooling (driven mostly by relationships between young mothers and their sons) and no effect for father's schooling. Also the precision of estimates increases. These results are logical as it sounds reasonable that the changes in compulsory years of schooling would have more effect in the lower educated groups. In another similar study made using change in the compulsory schooling law in Britain in 1957, Chevalier (2008) finds a large positive effect for mother's education on child's education and almost no effect of father's education.

Some instrumental variable studies explore the influence of additional years of compulsory education for parents on the probability that their children would repeat the same grade twice at school. For example, the study by Oreopoulos et al. (2006) uses U.S. compulsory schooling reforms and finds that the influences of the mother' s and father' s schooling on their children's grade repetition are equally important. Another study (Maurin and McNally, 2008) addresses grade repetition as outcome but uses variation in parental higher education as predictive variable. The study uses as instruments the county by- year variation in tuition fees and college location, and the results suggest that parental education matters in lowering the probability of grade repetition.

To sum up, the instrumental variable studies which use variations in compulsory years of education of parents seem to be capturing the effect of increase in years of education for the lower educated parents. The educational reforms affect most the lower educated layers on population, whereas those who obtain higher education would likely do so whether the reform was implemented or not.

7. Conclusion

7.1. Lessons learned from intergenerational regressions for adoptees

This study reviewed seven papers that estimate intergenerational regressions for educational attainments of adopted children. These papers compare the strength of intergenerational transmission of education for adoptees to the strength of intergenerational transmission of education for non-adoptees with the aim to discover the relative importance of nature (genetic endowments) and nurture (upbringing) in intergenerational associations of education. The idea is that any statistical dependence between the years of education of adoptive parents and their adopted children is driven by the effect of upbringing, whereas magnitude of the difference in intergenerational transmission of educational attainment for adoptees comparing to non-adoptees represents the effect of genetic endowments on educational achievement. The reviewed studies indeed find that intergenerational transmission of education is lower for adoptees comparing to non-adoptees. This suggests that some part of the intergenerational associations of education is driven by inherited abilities. At the same time, the reviewed adoptee studies find positive and statistically significant schooling effects when mother's and father's schooling are included as separate regressors, which suggests that upbringing also plays a role in educational achievement. With the assumption that the models are correctly specified, the estimates on how much family inheritable endowments contribute to the intergenerational schooling association range from 30 to 80 percent, but the majority of estimates are close to 50 percent. These percentages are inclusive of educational attainment passed through the assortative mating. When the assortative mating is controlled for by including simultaneously education of both parents as included into regression, they studies find that mother's schooling effect falls relatively more comparing to father's schooling effect. This finding is contrary to a common belief that mothers' education is especially important for children's education. In addition, Björklund et al. (2006) estimate directly the effect of nature on education by regressing adoptees education on education of their birth parents. They find about half of the transmission of education to adoptees works through biological parents and about half works through adoptive parents.

I conducted a replication of some of the results published in Sacerdote (2007). The sample used in Sacerdote (2007) was publicly available, and I performed intergenerational regression of educational outcomes for Korean-American adoptees and own-birth children in that sample. The regressions were estimated for both mothers and fathers', whereas Sacerdote (2007) estimates the intergenerational regressions for mothers only. The results for mothers were very similar to the results published in Sacerdote (2007) and indicate that mother's educational has a small positive effect on education of adopted children's, whereas the results for fathers did not capture any effect of father's education on education of adopted children. The absence of effect of paternal education is surprising, since the previous studies of adoptees have found a positive effect of adoptive father's education of education of adoptive children. On the other hand, only one of the other studies was done on a sample of children adopted from abroad (Holmlund et al. 2011), and the effect of adoptive parents' education on education of adoptees was substantially, from two to three times, lower in that study comparing to studies which included adoptees born in the same country where they grew up. This suggests that either transmission of education happens differently for children adopted from abroad, or the lower rate of selective placement in international adoptions purifies the estimated nurture effect from nature-related influences thus causing the estimated effect of nurture to decrease.

In overall, the results of adoptee studies imply that both genetics and family environment matter, and that their effects on educational attainment of children are about equal. However, these results are obtained with adoptee samples, and their applicability to the general population is limited. As adoptive parents and adoptive children are different on a number of characteristics from other parents and children, it is not clear to which degree the process of intergenerational transmission of education is similar for these two groups.

7.2. Implications of results for policymakers

According to Sacerdote (2011), many social scientists believe that differences in school quality and home environments can explain a large part of the inequality in educational outcomes. Estimates obtained with intergenerational regressions for adoptees do not contradict this viewpoint. As Sacerdote (2011) notes, in a way, the more we learn about the effects of rearing environment on children's outcomes, the more we see a picture that fits the existing parental intuition. However, from the policy making perspective, finding that intergenerational transmission of education happens partly through the influence of nurture raises the new questions. The future research lies in a better understanding the mechanisms that are responsible for parental schooling being passed on to the next generation (Holmlund et al. 2011). One natural mechanism to suggest would be the income, but education might also have effect on parenting style and the type of the role model that parents are for their children.

In addition, from practical point of view the main question is what would be results of different interventions. As Goldberger (1977), Björklund et al. (2005) and others have noted, finding the relative importance of nature and nurture on certain outcome does not inform policy makes regarding possibly policies that could improve the situation. For example, eyesight is determined genetically for the large part, but eyeglasses correct successfully and cost-efficiently the deficiencies in eyesight (Manski 2011). Similarly, there might potentially exist a way to counteract the unfavorable genetic endowments of family environment and to improve the children’s chances for higher education. However, the methodology of the reviewed studies does not enable us to address the issue of potential interventions and their effects.

It can be concluded that current adoptee studies that estimate the intergenerational transmission of education are of limited practical use to policymakers. At the same time, the positive impact of upbringing environment on educational outcomes suggests that there could be room for social policies which decrease the dependence on children’s life chances (in terms of education) on the parents and family background.

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Attachments

Table 1. Estimates of transmission coefficients for years of schooling in reviewed studies

Adoptee samples from reviewed studies		Estimated OLS coefficients for years of schooling			
		Non-adoptees		Adoptees	
Study	Sample and number of observations	Mother-Child	Father-Child	Mother-Child	Father-Child
Holmlund et al. 2011	160 own-born children and 496 adopted children born in Sweden. Average birth year 1976. Sweden	0,28 (0,07)** _0,25_ _(0,08)**_	0,21 (0,09)* _0,11_ _(0,09)_	0,11 (0,03)** _0,05_ _(0,04)_	0,1 (0,03)** _0,06_ _(0,04)+_
Holmlund et al. 2011	912 own-birth children and 4893 adopted children born abroad. Average birth year 1979. Sweden	0,22 (0,03)** _0,15_ _(0,04)**_	0,19 (0,03)** _0,13_ _(0,04)**_	0,04 (0,01)** _0,03_ _(0,01)**_	0,04 (0,01)** _0,04_ _(0,01)*_
Björklund et al. 2004	SAR: 148,496 own birth and 7498 adopted children all born in Sweden. Average birth year 1966. Sweden	0,24 (0,00)** _0,16_ _(0,00)**_	0,23 (0,00)** _0,16_ _(0,00)**_	0,11 (0,01)** _0,06_ _(0,01)**_	0,13 (0,01)** _0,1_ _(0,01)**_
Björklund et al. 2006	SAR: 94,079 own birth and 2125 adopted children all born in Sweden. Average birth year 1964. Sweden	0,243 (0,00)** _0,16_ _(0,00)**_	0,24 (0,00)** _0,17_ _(0,00)**_	0,074 (0,01)** _0,02_ _(0,01)_	0,114 (0,01)** _0,09_ _(0,01)**_
Sacerdote 2000	NLSY79: 5614 own birth and 170 adopted children. Average birth year 1961. US	0,35 (0,01)**	0,284 (0,01)**	0,22 (0,06)** _0,11_ _(0,07)_	0,161 (0,04)** _0,11_ _(0,04)*_
Sacerdote 2007	HICS: 1051 own birth and 1256 adopted children from Korea. Average birth year adopted and birth children: 1975 and 1969. US	0,315 (0,04)**	n.a.	0,089 (0,03)**	n.a.
Plug 2004	WLS: 15,871 own birth and 369 adopted. Average birth year adopted and birth children: 1969 and 1965. US	0,538 (0,02)** _0,3_ _(0,02)**_	0,39 (0,01)** _0,3_ _(0,01)**_	0,276 (0,10)** _0,1_ _(0,08)_	0,27 (0,04)** _0,23_ _(0,04)**_
Dearden et al. 1997	NCDS: 4030 own birth sons and 41 adopted sons. Birth year: 1958. UK		0,42 (0,02)**		0,356 (0,12)**

Blue italics: control for assortative mating, mother's and father's years of education are included simultaneously into regression

Table 2. Transmission of education between adopted child and biological parents

	Non-adoptees 94,079 obs.	Adoptees 2125 obs.
Biological mother	0,234** (0,002) *0,158*** *(0,002)*	0,132** (0,017) *0,101*** *(0,017)*
Biological father	0,240** (0,002) *0,170*** *(0,002)*	0,113** (0,016) *0,094*** *(0,016)*
Adoptive mother	Not applicable	0,074** (0,014) *0,021* *(0,015)*
Adoptive father	Not applicable	0,114** (0,013) *0,094*** *(0,014)*

(standard error)

*indicates significance at 5 percent level, and ** 1 percent level

Blue italics: control for assortative mating

Table 3. Regression output from Stata.

Regression of adopted child's years of education on mother's years of education.

Linear regression

Number of obs	= 1023
F(35, 796)	= .
Prob > F	= .
R-squared	= 0.0564
Root MSE	= 2.114

(Std. Err. adjusted for 797 clusters in id)

higradechild	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
M_higrade	.0782543	.0286126	2.73	0.006	.0220893	.1344194
malechild	-.6627773	.163989	-4.04	0.000	-.9846794	-.3408752
a26	.3238584	.5813781	0.56	0.578	-.817357	1.465074
a27	.7796983	.5757141	1.35	0.176	-.350399	1.909796
a28	.2206181	.5824288	0.38	0.705	-.9226596	1.363896
a29	.3561031	.5722868	0.62	0.534	-.7672666	1.479473
a30	.3921737	.5720361	0.69	0.493	-.7307038	1.515051
a31	.6280717	.5741018	1.09	0.274	-.4988607	1.755004
a32	.5501491	.5965746	0.92	0.357	-.6208962	1.721194
a33	.1442043	.6062035	0.24	0.812	-1.045742	1.334151
a34	.6550832	.6653372	0.98	0.325	-.6509396	1.961106
a35	-.2254089	.7379553	-0.31	0.760	-1.673977	1.223159
a36	.2688931	.7382231	0.36	0.716	-1.180201	1.717987
a37	.0730927	.8232867	0.09	0.929	-1.542977	1.689162
a38	.4548339	.8835675	0.51	0.607	-1.279564	2.189231
a39	-.2197318	1.219181	-0.18	0.857	-2.612922	2.173458
a40	.4518036	.9179366	0.49	0.623	-1.350059	2.253666
ay64	-1.741522	.8633788	-2.02	0.044	-3.43629	-.0467538
ay65	-2.067172	1.16924	-1.77	0.077	-4.362331	.2279867
ay66	-2.213515	1.460189	-1.52	0.130	-5.07979	.6527614
ay67	-.4443699	1.010976	-0.44	0.660	-2.428865	1.540125
ay68	-1.352516	.9874554	-1.37	0.171	-3.29084	.5858085
ay69	-1.240344	.984253	-1.26	0.208	-3.172382	.6916939
ay70	-2.036492	.8886286	-2.29	0.022	-3.780824	-.2921597
ay71	-1.413795	.8486808	-1.67	0.096	-3.079712	.2521216
ay72	-1.573382	.8234729	-1.91	0.056	-3.189817	.043053
ay73	-1.361787	.8060772	-1.69	0.092	-2.944075	.2205014
ay74	-1.082136	.8348921	-1.30	0.195	-2.720986	.5567143
ay75	-1.232498	.8328139	-1.48	0.139	-2.867269	.4022727
ay76	-1.088174	.8455211	-1.29	0.198	-2.747888	.5715409
ay77	-.9361928	.8991033	-1.04	0.298	-2.701087	.8287009
ay78	-.9383338	.8880739	-1.06	0.291	-2.681577	.8049096
ay79	-3.528563	.9088058	-3.88	0.000	-5.312503	-1.744624
ay80	-2.72407	1.265306	-2.15	0.032	-5.2078	-.24034
ay81	-1.775349	1.27366	-1.39	0.164	-4.275477	.7247799
ay82	-.2700084	1.76453	-0.15	0.878	-3.733691	3.193674
ay83	-3.451571	1.180899	-2.92	0.004	-5.769614	-1.133527
ay84	(omitted)					
ay85	(omitted)					
ay86	-.09061	.8655355	-0.10	0.917	-1.789612	1.608392
_cons	14.95264	1.03761	14.41	0.000	12.91586	16.98941

With control for child's gender, year of birth and year of arrival to U.S.

Clustered at family level.

Table 4. Regression output from Stata.

Regression of adopted child's years of education on father's years of education.

```
Linear regression                                      Number of obs =    1010
                                                       F( 35,   787) =       .
                                                       Prob > F      =       .
                                                       R-squared     =  0.0466
                                                       Root MSE      =  2.1245

                                   (Std. Err. adjusted for 788 clusters in id)
```

higradechild	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
F_higrade	.0280646	.024991	1.12	0.262	-.0209923	.0771215
malechild	-.625804	.1635489	-3.83	0.000	-.9468477	-.3047602
a26	.3689356	.5905758	0.62	0.532	-.7903546	1.528226
a27	.846026	.5757859	1.47	0.142	-.2842318	1.976284
a28	.3248329	.5809372	0.56	0.576	-.8155368	1.465203
a29	.407411	.5755484	0.71	0.479	-.7223806	1.537203
a30	.4686711	.5757838	0.81	0.416	-.6615826	1.598925
a31	.677783	.5781583	1.17	0.241	-.4571319	1.812698
a32	.5791899	.5987433	0.97	0.334	-.5961329	1.754513
a33	.1213921	.6122068	0.20	0.843	-1.080359	1.323144
a34	.6288416	.6683473	0.94	0.347	-.6831127	1.940796
a35	-.0891735	.7677595	-0.12	0.908	-1.596272	1.417925
a36	.334038	.7569803	0.44	0.659	-1.151901	1.819977
a37	.0828643	.8290856	0.10	0.920	-1.544617	1.710345
a38	.5120355	.8931673	0.57	0.567	-1.241237	2.265308
a39	-.2734487	1.266138	-0.22	0.829	-2.758857	2.211959
a40	.4984576	.9323175	0.53	0.593	-1.331666	2.328581
ay64	-1.783149	.905332	-1.97	0.049	-3.560301	-.0059982
ay65	-2.13849	1.150418	-1.86	0.063	-4.39674	.1197606
ay66	-2.321163	1.47775	-1.57	0.117	-5.22196	.579634
ay67	-.5223348	1.034696	-0.50	0.614	-2.553426	1.508756
ay68	-1.329574	1.037942	-1.28	0.201	-3.367036	.7078878
ay69	-1.081839	1.052737	-1.03	0.304	-3.148343	.9846647
ay70	-1.869784	.9363972	-2.00	0.046	-3.707916	-.0316524
ay71	-1.383392	.892793	-1.55	0.122	-3.135929	.3691458
ay72	-1.531561	.8728363	-1.75	0.080	-3.244923	.181802
ay73	-1.367734	.8548793	-1.60	0.110	-3.045848	.3103794
ay74	-1.085075	.8816341	-1.23	0.219	-2.815708	.6455577
ay75	-1.1778	.8798771	-1.34	0.181	-2.904984	.5493835
ay76	-1.130222	.8934366	-1.27	0.206	-2.884023	.6235784
ay77	-.941762	.9463376	-1.00	0.320	-2.799407	.9158826
ay78	-.8295257	.940227	-0.88	0.378	-2.675175	1.016124
ay79	-3.454672	.9680374	-3.57	0.000	-5.354912	-1.554431
ay80	-2.697155	1.298951	-2.08	0.038	-5.246973	-.1473367
ay81	-1.748325	1.294992	-1.35	0.177	-4.290372	.7937221
ay82	.0707627	1.877014	0.04	0.970	-3.613783	3.755308
ay83	-3.300899	1.201494	-2.75	0.006	-5.659411	-.9423861
ay84	(omitted)					
ay85	(omitted)					
ay86	.0713967	.9090373	0.08	0.937	-1.713028	1.855821
_cons	15.60864	1.051098	14.85	0.000	13.54535	17.67192

With control for child's gender, year of birth and year of arrival to U.S.

Clustered at family level.

Table 5. Regression output from Stata.

Regression of adopted child's years of education on mother's and father's years of education (control for assortative mating).

```
Linear regression                                      Number of obs =     1003
                                                       F( 36,   782) =        .
                                                       Prob > F      =        .
                                                       R-squared     =   0.0514
                                                       Root MSE      =   2.1224

                                     (Std. Err. adjusted for 783 clusters in id)
```

higradechild	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
M_higrade	.076549	.0324924	2.36	0.019	.0127664	.1403317
F_higrade	-.0048108	.028012	-0.17	0.864	-.0597984	.0501768
malechild	-.6297995	.1651744	-3.81	0.000	-.9540372	-.3055619
a26	.3407715	.585076	0.58	0.560	-.8077339	1.489277
a27	.8000703	.5728314	1.40	0.163	-.3243989	1.92454
a28	.2596935	.5817952	0.45	0.655	-.8823717	1.401759
a29	.3932374	.5715542	0.69	0.492	-.7287248	1.5152
a30	.4470119	.5713391	0.78	0.434	-.674528	1.568552
a31	.6623182	.5740024	1.15	0.249	-.4644498	1.789086
a32	.5782868	.5959916	0.97	0.332	-.5916459	1.74822
a33	.1215306	.6086149	0.20	0.842	-1.073182	1.316243
a34	.6433282	.6648545	0.97	0.334	-.6617827	1.948439
a35	-.0129142	.7552481	-0.02	0.986	-1.495468	1.469639
a36	.3598101	.7473104	0.48	0.630	-1.107162	1.826782
a37	.0886269	.8224786	0.11	0.914	-1.5259	1.703154
a38	.4774511	.8789204	0.54	0.587	-1.247871	2.202774
a39	-.2181175	1.233153	-0.18	0.860	-2.638799	2.202564
a40	.4812438	.9157713	0.53	0.599	-1.316417	2.278905
ay64	-1.782194	.8674223	-2.05	0.040	-3.484946	-.0794423
ay65	-2.050077	1.176088	-1.74	0.082	-4.358739	.2585858
ay66	-2.19412	1.482314	-1.48	0.139	-5.103906	.715665
ay67	-.4555688	1.009123	-0.45	0.652	-2.436479	1.525341
ay68	-1.384685	1.007079	-1.37	0.170	-3.361583	.592213
ay69	-1.144466	1.002815	-1.14	0.254	-3.112994	.8240617
ay70	-1.917824	.9001641	-2.13	0.033	-3.684848	-.1507999
ay71	-1.395308	.8531253	-1.64	0.102	-3.069994	.2793792
ay72	-1.555982	.8293942	-1.88	0.061	-3.184084	.072121
ay73	-1.37888	.8122028	-1.70	0.090	-2.973236	.2154761
ay74	-1.119094	.8417058	-1.33	0.184	-2.771364	.5331763
ay75	-1.20892	.8392442	-1.44	0.150	-2.856358	.4385184
ay76	-1.101041	.8547785	-1.29	0.198	-2.778973	.5768907
ay77	-.9361666	.9110854	-1.03	0.304	-2.724629	.852296
ay78	-.8428631	.9010675	-0.94	0.350	-2.611661	.9259345
ay79	-3.498193	.9319727	-3.75	0.000	-5.327658	-1.668729
ay80	-2.718932	1.267744	-2.14	0.032	-5.207517	-.230348
ay81	-1.769606	1.27833	-1.38	0.167	-4.278971	.7397578
ay82	-.2473657	1.743962	-0.14	0.887	-3.670768	3.176036
ay83	-3.41426	1.175947	-2.90	0.004	-5.722647	-1.105874
ay84	(omitted)					
ay85	(omitted)					
ay86	-.1277322	.871728	-0.15	0.884	-1.838936	1.583472
_cons	15.01442	1.0513	14.28	0.000	12.95072	17.07813

With control for child's gender, year of birth and year of arrival to U.S.

Clustered at family level.