Family background and children's schooling outcomes

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Chapter 1

The effect of parents' schooling on child's schooling: A nonparametric bounds analysis

1.1 Introduction

Is there an effect of parents' schooling on the schooling of their child? This question has received much attention in the empirical literature. Most if not all studies find a positive association between parental and child's schooling. Haveman and Wolfe (1995) state in a survey of the literature

> *"....perhaps the most fundamental economic factor is the human capital of parents, typically measured by the number of years of schooling attained. This variable, emphasized in the earlier studies of the intergenerational transmission of socioeconomic status, is included in virtually every study described {in this review}; it is statistically significant and quantitatively important, no matter how it is defined."*– Haveman and Wolfe (1995, pp.1855).

Most of the studies discussed in the overview regress child's schooling on the schooling of the parents. To give a causal interpretation to the results of these regressions, one has to impose a number of assumptions; a linear impact of parental years of schooling and no correlation between parents' schooling and unobserved endowments affecting their child's schooling. Since these are rather strong assumptions, the positive association does not need to be a true causal relation. In an attempt to isolate the causal impact of parents' schooling, different identification strategies have been applied in the recent empirical literature.

One of the approaches is to use a sample of identical twins to eliminate the correlation between parental schooling and child's schooling attributable to genetics (Behrman and Rosenzweig (2002, 2005), Antonovics and Goldberger (2005)). These studies find a positive and significant relation between both father's and mother's schooling and the schooling of their child. However, the within-twin estimates, whereby they difference out the genetic factors, indicate that the effect of parents' schooling is lower than the OLS estimates and that this decline is strongest for mothers.

A second approach uses a sample of adoptees, whereby they exploit the fact that there is no genetic link between adoptive parents and their adopted child (Björklund *et al.* (2006), Sacerdote (2002, 2007), Plug (2004)). The main findings of these adoption studies are that the estimates of the relation between parents' and child's schooling is significantly smaller when estimated on a sample of adoptees instead of on a sample of own birth children. This indicates that a large part of the intergenerational association is due to genetic transmission of endowments.

A third identification strategy is an instrumental variable (IV) approach. By using a change in compulsory schooling laws in Norway as instrument, Black *et al.* (2005A) find insignificant effects of parental schooling on child's years of schooling, except for the effect of mother's schooling on the schooling of her son. Chevalier (2004) uses a change in the minimum school leaving age in Britain and finds that the effects of parents' schooling on the probability that the child of the same gender has post-compulsory schooling is positive and higher than the results without using an instrument. Oreopoulos *et al.* (2006), Carneiro *et al.* (2007) and Maurin and McNally (2008) focus on the effect of parents' schooling on intermediate schooling outcomes. They all find a significant impact of parents' schooling and most of the IV estimates are somewhat higher than the OLS results.

These identification methods generally put strong requirements on the data, since one needs a data set that includes information on both parents' and child's completed schooling, that includes a large enough sample of twins or adoptees, or that includes good instruments for schooling, which are scarce. And even when these rich data sources are available one still has to impose a number of assumptions to be able to use these methods to say something about the causal impact of parents' schooling.

The method using within-twin differences to identify the effect of parents' schooling strongly relies on the assumption of a linear impact of parents' years of schooling. This implies that an extra year of primary education should have the same effect as an extra year of university education. But is this plausible? Another assumption that these twin studies have to make is that there are no interaction effects between genetic endowments and the schooling level of the parents. These studies further assume that monozygotic twin mothers and fathers have identical unobserved endowments and that all differences in schooling levels between these twin parents are exogenous. This has been questioned for example by Bound and Solon (1999).

Studies using samples of adoptees assume that adoptees are randomly assigned to their adoptive parents. This assumption might be violated when adoption agencies match adoptees to adoptive parents on the basis of characteristics of the biological parents. Another assumption which is necessary to give a causal interpretation to the results is that parents' child rearing talents must be uncorrelated to their level of schooling. Also many of these studies rule out potential interaction effects between heritable endowments and the environment in which the children are raised, something which has been criticized in the literature (Cunha and Heckman (2007)).[1]

[1] Björklund *et al.* (2006) use a sample of Swedish adoptees to estimate intergenerational mobility. They have information on the adoptive and biological parent of the adoptees and include an interaction term in their analysis. They find some evidence for a positive interaction effect between pre-birth factors and post-birth environment.

When using an instrumental variable approach one generally does not have to impose these assumptions, but instrumental variables are often only able to identify a local average treatment effect. Also whether one can interpret the results of IV studies as causal depends on the validity of the instruments something which can, unfortunately, not be tested.

This chapter uses a different approach to investigate the effect of parents' schooling on child's schooling; a nonparametric bounds analysis based on Manski and Pepper (2000), using the most recent version of the Wisconsin Longitudinal Study. We start with making no assumptions and then add much weaker and testable assumptions to tighten the bounds. The assumptions are much weaker in the sense that they do not impose a linear effect of parents' schooling, they allow for a potential positive correlation between parents' schooling and unobserved endowments and they allow for possible interaction effects between heritable endowments and parents' level of schooling. Also, in contrast to most instrumental variable studies, we are able to identify bounds on the effect of parents' schooling over the entire schooling distribution.

There is a trade-off between making less strong (and more credible) assumptions and the information one obtains about the effect of interest. This chapter will obtain bounds instead of point identification. The contribution of this chapter is that it makes relatively weak and testable assumptions, while the identification strategies mentioned above are based on much stronger assumptions and give point estimates which are only informative if these assumptions are correct. And, although there have been studies applying a nonparametric bounds analysis (Gerfin and Schellhorn (2006), González (2005), Pepper (2000), Lechner (1999), Blundell *et al.* (2007)), this chapter is the first study investigating intergenerational schooling mobility using a nonparametric bounds analysis.

The remainder of the chapter is organized as follows. Section 1.2 gives the empirical specification. Section 1.3 gives a description of the data. Section 1.4 will give the results of the nonparametric bounds analysis and compares them to the results of an exogenous treatment selection assumption. And finally Section 1.5 will summarize and conclude.

1.2 Empirical specification

For each child we have a response function $y_i(.) : T \rightarrow Y$ which maps treatments $t \in T$ into outcomes $y_i(t) \in Y$. Where the treatment t is the level of schooling of the parent and y is years of schooling of the child. For each child we observe the realized level of parental schooling z_i and his realized years of schooling $y_i \equiv y_i(z_i)$, but we do not observe the potential outcomes $y_i(t)$ for $t \neq z_i$. To simplify notation the subscript i will be dropped in the following.

We are interested in the mean effect of an increase in parental schooling from s to t on child's schooling, that is

$$\triangle(s,t) = E\left[y(t)\right] - E\left[y(s)\right] \tag{1.1}$$

By using the law of iterated expectations and the fact that $E[y(t)|z=t] = E[y|z=t]$ we can write

$$E\left[y(t)\right] = E[y|z=t] \cdot P(z=t) + E[y(t)|z \neq t] \cdot P(z \neq t) \tag{1.2}$$

With a data set where we observe the schooling of a child and his parent we can observe the mean schooling of a child whose parent has schooling level t and the probability that the parent has schooling level t. However, for a child with a parent who does not have schooling level t we cannot observe what his mean schooling would have been if his parent would have had schooling level t. That is, we cannot observe $E[y(t)|z \neq t]$. It is only possible to say more about the effect of interest by augmenting the things that are observed with assumptions.

Manski (1989) shows though that it is possible to identify bounds on $E\left[y(t)\right]$ without making any assumptions if the support of the dependent variable is bounded, which is the case with child's schooling. By substituting $E[y(t)|z \neq t]$ by the lowest possible level of education $\underline{y}$ we obtain a lower bound on $E\left[y(t)\right]$ and by replacing it with the highest possible level of schooling $\bar{y}$ we obtain the upper bound. This gives Manski's no-assumption bounds (1989)

No-assumption bounds

$$
\begin{gathered}
E[y|z=t]\cdot P(z=t)+\underline{y}\cdot P(z\neq t) \\
\leq E\,[y(t)] \leq \\
E[y|z=t]\cdot P(y=t)+\overline{y}\cdot P(z\neq t)
\end{gathered}
\tag{1.3}
$$

To tighten these no-assumption bounds we will subsequently add the monotone treatment response assumption (MTR) and the monotone treatment selection assumption (MTS) which are introduced and derived in Manski (1997) and Manski and Pepper (2000).

The monotone treatment response assumption states that a child's schooling is weakly increasing in conjectured schooling of his parent:

$$t_2 \geq t_1 \Rightarrow y(t_2) \geq y(t_1) \tag{1.4}$$

This assumes that having a higher educated parent never decreases a child's schooling, which is also suggested by human capital theory (Becker and Tomes (1979), Solon (1999)). A zero effect is not ruled out by this assumption. The MTR assumption implies the following

$$\text{for } u<t \qquad E[y(t)|z=u] \geq E[y(u)|z=u] = E[y|z=u]$$

$$\text{so } E[y(t)|z=u] \in [E[y|z=u]\ ,\ \overline{y}]$$

$$\text{for } u>t \qquad E[y(t)|z=u] \leq E[y(u)|z=u] = E[y|z=u]$$

$$\text{so } E[y(t)|z=u] \in [\ \underline{y}\ ,\ E[y|z=u]]$$

A sample of children and their parents can be divided into three groups; (1) children with a parent that has a schooling level lower than t, (2) those that have a parent with a schooling level equal to t, and (3) children who have a parent with a schooling level higher than t. For the second group we observe the effect on mean schooling of having a parent with schooling level t. For the first group we know that under the MTR assumption their observed mean schooling is less than or equal to what their mean schooling would have been if their parent did have schooling level t. So we can use the mean schooling we observe for this first group to tighten the lower bound. For the third group we know that if they would have had a parent with schooling level t, their mean schooling would have been lower than or equal to their current mean schooling. We can therefore use the mean schooling we observe for this third group to tighten the upper bound. By combining this with the no-assumption bounds above we get the MTR bounds:

MTR bounds

$$\begin{gathered} E[y|z<t]\cdot P(z<t)+E[y|z=t]\cdot P(z=t)+\underline{y}\cdot P(z>t) \\ \leq E\left[y(t)\right]\leq \\ \bar{y}\cdot P(z<t)+E[y|z=t]\cdot P(z=t)+E[y|z>t]\cdot P(z>t) \end{gathered} \tag{1.5}$$

To narrow the bounds we will add the monotone treatment selection assumption. Under this assumption children with higher schooled parents have weakly higher mean schooling functions than those with lower schooled parents:

$$u_2 \geq u_1 \Rightarrow E\left[y(t)|z=u_2\right] \geq E\left[y(t)|z=u_1\right] \tag{1.6}$$

This assumption is consistent with higher schooled parents having higher heritable and child-rearing endowments which can positively (but not negatively) affect their child's schooling. Under the combined MTR-MTS assumption the following holds.[2]

$$\text{for } u < t \quad E[y(t)|z=t] \geq E[y(t)|z=u] \geq E[y(u)|z=u]$$

$$\text{so } E[y(t)|z=u] \in [E[y|z=u]\ ,\ E[y|z=t]]$$

$$\text{for } u > t \quad E[y(t)|z=t] \leq E[y(t)|z=u] \leq E[y(u)|z=u]$$

$$\text{so } E[y(t)|z=u] \in [E[y|z=t]\ ,\ E[y|z=u]]$$

We can again divide the sample into three groups, children who have a parent with a schooling level lower than t, equal to t, or higher than t. If the schooling of the parents of the first group would be increased to t, we know by the MTS assumption that the mean schooling of the children would be weakly lower than the mean schooling we observe for the children who currently have a parent with schooling level t. We can therefore use the mean schooling we observe for the children who have a parent with schooling level t as an upper bound on the treatment effect for the first group. Similarly we can use it as a lower bound on the treatment effect for the third group. By combining the monotone treatment response assumption and the monotone treatment selection assumption we get the MTR-MTS bounds:[3]

[2]The first inequalities follow from the MTS assumption and the second inequalities from the MTR assumption.

[3]For a full derivation of the MTR and MTR-MTS bounds see Manski (1997) and Manski and Pepper (2000).

MTR-MTS bounds

$$
\begin{gathered}
E[y|z<t]\cdot P(z<t)+E[y|z=t]\cdot P(z=t)+\ E[y|z=t]\cdot P(z>t) \\
\leq E\left[y(t)\right] \leq \\
E[y|z=t]\cdot P(z<t)+E[y|z=t]\cdot P(z=t)+E[y|z>t]\cdot P(z>t)
\end{gathered} \tag{1.7}
$$

It is possible to test the combined MTR-MTS assumption. Under the MTR-MTS assumption the following holds

$$\text{for } u_2 > u_1$$

$$E[y|z=u_2]=E[y(u_2)|z=u_2]\geq E[y(u_2)|z=u_1]\geq E[y(u_1)|z=u_1]=E[y|z=u_1]$$

So under the MTR-MTS assumption the mean schooling of a child should be weakly increasing in the realized level of schooling of the parent, if this is not the case the MTR-MTS assumption should be rejected.

So far we have obtained bounds on $E\left[y(t)\right]$ but we are interested in the effect of an increase in parental schooling $(E[y(t)]-E\left[y(s)\right])$. To obtain bounds on this treatment effect we will subtract the lower (upper) bound on $E\left[y(s)\right]$ from the upper (lower) bound on $E[y(t)]$ to get the upper (lower) bound. For the bounds using the MTR assumption the lower bound on the effect of an increase in parents' education cannot be negative and is therefore set to zero.

Monotone instrumental variable assumption

Suppose we observe not only the schooling of the child and his parent but also a variable z^*. We could then divide the sample into sub-samples, one for each value of z^*, and for each sub-sample obtain the no-assumption bounds on the basis of equation (1.3). It may well be that the no-assumption bounds are relatively tight for some sub-samples but relatively wide for other sub-samples. We could exploit this variation in the bounds over the sub-samples if z^* satisfies the instrumental variable assumption (Manski and Pepper (2000)). A variable z^* satisfies the instrumental variable assumption, in the sense of mean-independence, if it holds that for all treatments $t \in T$ and all values of the instrument $m \in M$

$$E\left[y(t)|z^* = m\right] = E\left[y(t)\right] \tag{1.8}$$

This means that the schooling function of the child should be mean-independent of the variable z^*. If z^* satisfies the instrumental variable assumption, we can obtain an IV-lower bound on $E\left[y(t)\right]$ by taking the maximum lower bound over all sub-samples and an IV-upper bound by taking the minimum upper bound over all sub-samples. Combining the instrumental variable assumption with the no-assumption bounds gives thus the following IV-bounds

IV-bounds

$$\begin{gathered} max_{m \in M}\left(E[y|z=t,\, z^*=m] \cdot P(z=t|z^*=m) + \underline{y} \cdot P(z \neq t|z^*=m)\right) \\ \leq E\left[y(t)\right] \leq \\ min_{m \in M}\left(E[y|z=t,\, z^*=m] \cdot P(z=t|z^*=m) + \overline{y} \cdot P(z \neq t|z^*=m)\right) \end{gathered} \tag{1.9}$$

The width of the no-assumption bounds depends on the proportion of children who actually have a parent with schooling level t. The higher $P(z=t)$ the tighter the no-assumption bounds. If for some sub-samples (defined by the values of z^*) the proportion of children who have a parent with schooling level t is higher than for other sub-samples, the no-assumption bounds will be tighter for these sub-samples. The IV-bounds will therefore be tighter than the no-assumption bounds if there is variation in $P(z=t|z^*=m)$ over z^*. This means that the probability that the parent has a certain level of schooling should vary with the value of the instrumental variable.

Since it is difficult to find a variable which satisfies the instrumental variable assumption in equation (1.8) we will use a weaker version; the monotone instrumental variable assumption. A variable z^* is a monotone instrumental variable (MIV) in the sense of mean-monotonicity if it holds that

$$m_1 \leq m \leq m_2 \Rightarrow E\left[y(t)|z^*=m_1\right] \leq E\left[y(t)|z^*=m\right] \leq E\left[y(t)|z^*=m_2\right] \tag{1.10}$$

So instead of assuming mean-independence, the monotone instrumental variable assumption allows for a weakly monotone relation between the variable z^* and the mean schooling function of the child (Manski and Pepper (2000)).

We can again divide the sample into sub-samples on the basis of z^* and obtain no-assumption bounds for each sub-sample. From equation (1.10) it follows that $E\left[y(t)|z^*=m\right]$ is no lower than the no-assumption lower bound on $E\left[y(t)|z^*=m_1\right]$ and it is no higher than the no-assumption upper bound on $E\left[y(t)|z^*=m_2\right]$. For the sub-sample where z^* has the value m we can thus obtain a new lower bound, which is the largest lower bound over all the sub-samples where z^* is lower than or equal to m. Similarly we can obtain a new upper bound by taking the smallest upper bound over all sub-samples with a value of z^* higher than or equal to m.

By repeating this for all $m \in M$ and taking the average we get the following MIV-bounds.

MIV-bounds

$$\sum_{m \in M} P(z^* = m) \cdot \left[max_{m_1 \leq m} \begin{pmatrix} E[y|z=t, z^* = m_1] \cdot P(z=t|z^* = m_1) \\ +\underline{y} \cdot P(z \neq t|z^* = m_1) \end{pmatrix} \right]$$

$$\leq E\left[y(t)\right] \leq \tag{1.11}$$

$$\sum_{m \in M} P(z^* = m) \cdot \left[min_{m_2 \geq m} \begin{pmatrix} E[y|z=t, z^* = m_2] \cdot P(z=t|z^* = m_2) \\ +\overline{y} \cdot P(z \neq t|z^* = m_2) \end{pmatrix} \right]$$

These MIV bounds are generally wider than the IV bounds. However when the no-assumption upper and lower bounds weakly decrease with the value of z^*, the identifying power of the MIV assumption is as strong as the identifying power of the IV assumption.[4]

Instead of combining the MIV assumption with the no-assumption bounds we can also combine the MIV assumption with the MTR-MTS bounds. This means that instead of obtaining no-assumption bounds for each sub-sample we obtain MTR-MTS bounds for each sub-sample. By replacing the no-assumption bounds in equation (1.11) by the MTR-MTS bounds we obtain the MTR-MTS-MIV bounds.

[4]The no-assumption lower bound is high when $P(z=t)$ is high. So for the lower bound to weakly decrease with the value of z^*, $P(z=t|z^*=m)$ should *decrease* for at least some values of z^*. The no-assumption upper bound is low when $P(z=t)$ is high. So for the upper bound to be weakly decreasing with z^*, $P(z=t|z^*=m)$ should *increase* for at least some values of z^*.

MTR-MTS-MIV bounds

$$\sum_{m\in M} P(z^*=m)\cdot\left[max_{m_1\leq m}\begin{pmatrix} E[y|z<t,\ z^*=m_1]\cdot P(z<t|\ z^*=m_1)+ \\ E[y|z=t,\ z^*=m_1]\cdot P(z=t|z^*=m_1)+ \\ E[y|z=t,\ z^*=m_1]\cdot P(z>t|\ z^*=m_1) \end{pmatrix}\right]$$

$$\leq E\left[y(t)\right]\leq \tag{1.12}$$

$$\sum_{m\in M} P(z^*=m)\cdot\left[min_{m_2\geq m}\begin{pmatrix} E[y|z=t,\ z^*=m_2]\cdot P(z<t|z^*=m_2)+ \\ E[y|z=t,\ z^*=m_2]\cdot P(z=t|z^*=m_2)+ \\ E[y|z>t,\ z^*=m_2]\cdot P(z>t|\ z^*=m_2) \end{pmatrix}\right]$$

We will use two monotone instrumental variables. The first is the schooling of the grandparent. Since it is unlikely that the schooling function of the child is mean-independent of the schooling of his grandparent we will not use grandparent's schooling as an instrumental variable, but we will use it as a monotone instrumental variable. By using grandparent's schooling as a MIV we assume that the mean schooling function of the child is monotonically increasing (or non-decreasing) in the schooling of the grandparent.

The second MIV is the schooling of the spouse. When we obtain bounds on the effect of mother's schooling we will use the level of schooling of the father as MIV, and if we obtain bounds on the effect of father's schooling we will use the schooling level of the mother as MIV. As with grandparent's schooling the schooling of the spouse is unlikely to satisfy the mean-independence assumption in equation (1.8), we will therefore use it as a MIV and assume that the mean schooling function of the child is non-decreasing in the schooling of the spouse.

Obtaining bounds on the effect of increasing father's/mother's schooling from s to t

works in the same way as was described at the end of the previous subsection. We first obtain the MTR-MTS-MIV upper and lower bounds on $E[y(t)]$ and $E[y(s)]$, and then take the difference between the upper bound on $E[y(t)]$ and the lower bound on $E[y(s)]$ to get the upper bound on $\triangle(s,t)$=$(E[y(t)] - E[y(s)])$. The lower bound on $\triangle(s,t)$ is set to zero by the monotone treatment response assumption.[5]

1.3 Data

The analysis in this chapter uses the most recent version of the Wisconsin Longitudinal Study (WLS). The WLS is a long-term study based on a random sample of 10,317 men and women who graduated from Wisconsin high schools in 1957. Next to information about the graduates the sample contains comparable data for a randomly selected sibling of most of the respondents. Survey data were collected from the original respondents in 1957, 1964, 1975, 1992, and 2004 and from the selected siblings in 1977, 1994, and 2005. We will mainly use the data from the last two waves (2004, 2005) since these contain updated information about completed schooling of the graduates and their spouses, the selected siblings and their spouses and about the children of both the graduates and the selected siblings. In the last two waves information is collected from 7,265 graduates and 4,271 selected siblings.

The sample that is used in this chapter includes graduates and selected siblings who were married at least once and who have at least one child. It is not possible to link children to spouses, but only possible to link children to respondents and spouses to respondents.

[5] This means that we do *not* use the following assumption to obtain bounds on $\triangle(s,t)$, which is stronger than the assumption in equation (1.10):

$$m_1 \leq m \leq m_2 \Rightarrow E\left[\triangle(s,t)|z^* = m_1\right] \leq E\left[\triangle(s,t)|z^* = m\right] \leq E\left[\triangle(s,t)|z^* = m_2\right] \tag{1.13}$$

Using assumption (1.13) instead of assumption (1.10) would mean that we obtain bounds on the effect of an increase in father's/mother's schooling ($\triangle(s,t)$) for each sub-sample and thus conditional on the monotone instrumental variable. This could be problematic when using the schooling of the spouse as MIV since part of the effect of increasing mother's (father's) schooling could be through the effect that she(he) marries a higher schooled spouse. However, since we do not use assumption (1.13) but instead use assumption (1.10), this is not an issue in the analysis in this chapter.

The sample is therefore further restricted to respondents who only have children from their first marriage to be quite sure that both the spouse and the respondent are the child's biological parents. This gives a final sample of 21,545 children of 5,167 graduates and 2,524 selected siblings.[6]

Information about completed schooling is available in years. For the analysis in this chapter it is necessary to have enough observations for each observed level of parental schooling, therefore we construct schooling variables in levels for the respondents and their spouses as follows:

1	Less than high school	< 12 years
2	High school	12 years
3	Some college	13-15 years
4	Bachelor's degree	16 years
5	Master's degree	17 years
6	More than Master's degree	>17 years

For the schooling of the grandparent we will use the schooling of the head of the household when the parent was 16 (in 80-90% of the cases the father is the head of the household).[7] We construct schooling variables in levels as with parents' schooling. However since the average schooling level has increased over time we construct different schooling levels for grandparents. The education variable for the head of the household has peaks at

[6]There are some children below the age of 23 and these children might still be in school. In the analysis we eliminate these observations. Chapter 2 shows that when 23% of the sample is censored, eliminating children who are still in school can cause a small positive bias. In the sample in this chapter only 1.5% is below the age of 23. It is unlikely that eliminating these observations can cause a significant bias in the estimates.

[7]Unfortunately this variable is not available for the spouse of the selected sibling

6, 8, 12 and 16 years of schooling, we therefore construct the following schooling variable in levels for the grandparent:

1	Elementary school	$\leq$6 years
2	Middle school	7-8 years
3	Some high school	9-11 years
4	Graduated from high school	12 years
5	Some college	13-15 years
6	Bachelor's degree or more	$\geq$ 16 years

Table 1.1 gives some descriptive statistics. Table 1.2 gives mean schooling of the child for each level of mother's and father's schooling and the percentage of observations in each category, and the appendix gives an overview of the educational system in the United States. For more detailed information on the WLS see Sewell *et al.* (2004) and WLS (2006) and the references therein.

Table 1.1: Summary Statistics

	Mean	Std. dev.	N
Years of schooling child	14.50	2.32	21,545
Child has bachelor's degree	0.46	0.50	21,545
Gender (female=1)	0.49	0.50	21,545
Age child	38.34	5.50	21,494
Years of schooling father	13.52	2.70	21,545
Years of schooling mother	13.03	1.86	21,545
Level of schooling father	2.87	1.43	21,545
Level of schooling mother	2.56	1.02	21,545
Schooling head of household when father was 16	9.86	3.40	14,614
Schooling head of household when mother was 16	9.88	3.40	16,912
Level of schooling head of household when father was 16	2.98	1.47	14,614
Level of schooling head of household when mother was 16	2.99	1.46	16,912

Table 1.2: Mean schooling child by schooling level mother/father (test of MTR-MTS assumption)

	Mothers		Fathers	
Schooling level parent	$E[y\|z=u]^a$	P(z=u)	$E[y\|z=u]^a$	P(z=u)
1: Less than high school (<12 years)	12.96	0.035	13.00	0.082
2: High school (12 years)	13.98	0.627	13.85	0.495
3: Some college (13-15 years)	15.19	0.158	14.85	0.142
4: Bachelor's degree (16 years)	15.93	0.131	15.59	0.141
5: Master's degree (17 years)	16.09	0.020	15.91	0.032
6: More than a Master's degree (>17 years)	16.29	0.028	16.36	0.107
N	*21,545*		*21,545*	

[a] MTR-MTS assumption not rejected

1.4 Results

In the analysis below we will compare the results of the nonparametric bounds analysis with the results of using an exogenous treatment selection assumption (ETS). The exogenous treatment selection assumption implies that $E[y(t)|z \neq t] = E[y|z=t]$ and yields point identification. It assumes that the schooling level of fathers and mothers is unrelated to unobserved factors affecting child's schooling (like child rearing talents or heritable endowments). Exogenous treatment selection is also assumed when regressing child's years of schooling on years of schooling of his parents. We will however not assume a linear effect of the years of schooling of the parent but instead estimate the effect of moving from one level of parental schooling to the next. Therefore we will compare the results of the bounds analysis with the results of an ETS assumption, which is the same as running OLS on child's schooling with one dummy variable for each level of mother's (father's) schooling.

Figures 1.1 and 1.2 show nonparametric bounds on mean years of schooling as a function of mother's (father's) level of schooling, compared to the exogenous treatment selection assumption. The no-assumption bounds as well as the MTR bounds are quite wide and do not give much information.[8] In the top-right panels the monotone treatment selection assumption is added to get the MTR-MTS bounds. As was already stated in Section 1.2 this combined MTR-MTS assumption can be tested as $E[y|z=u]$ must be weakly increasing in u. Table 1.2 shows that the MTR-MTS assumption is not rejected as average years of child's schooling is indeed weakly increasing both in the level of mother's schooling as in the level of father's schooling.

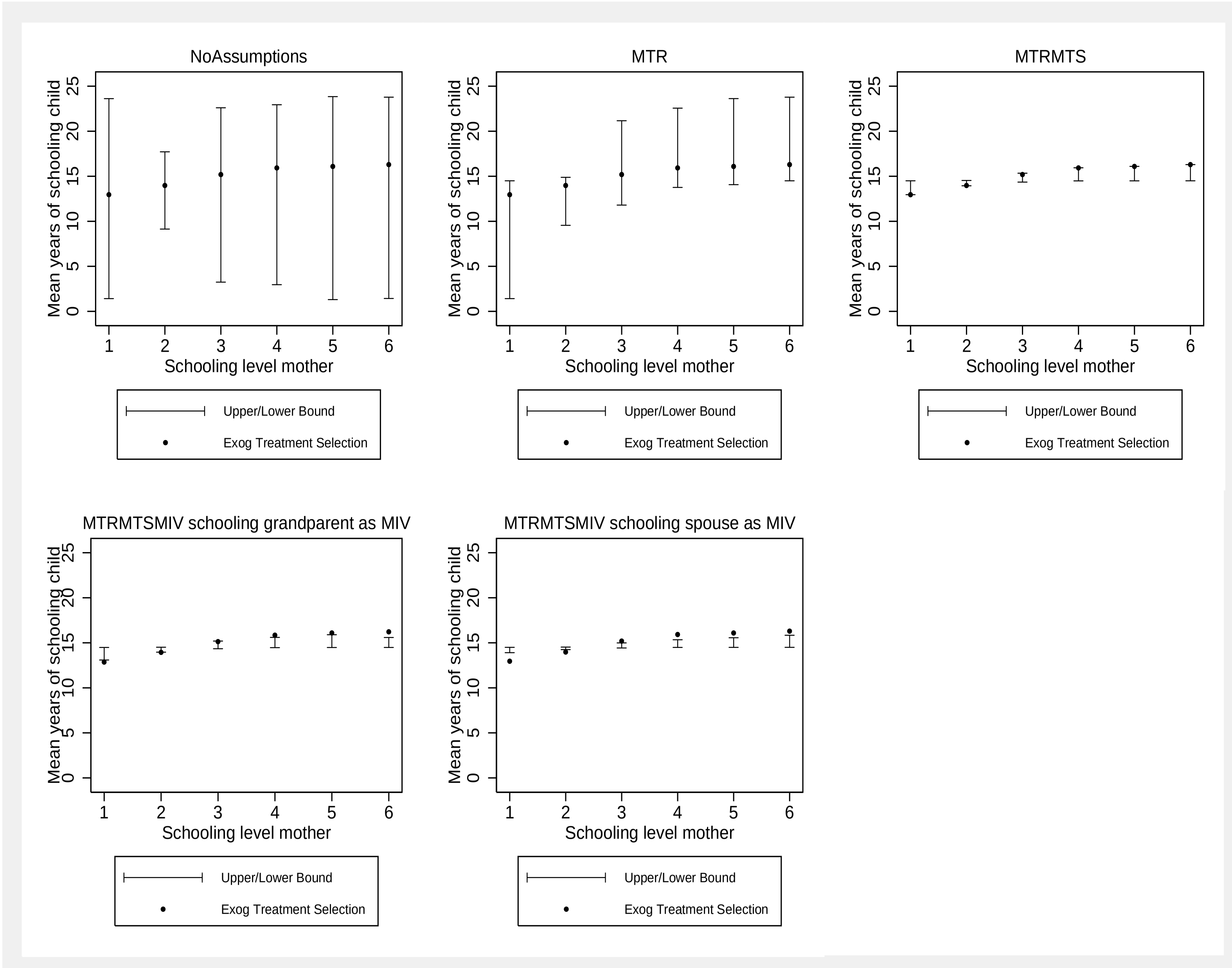
Adding the monotone treatment selection assumption strongly reduces the width of the bounds as is shown in the top-right panels of Figures 1.1 and 1.2. For the lowest levels of mother's and father's schooling the exogenous treatment selection point estimates almost coincide with the lower bounds, while for the highest levels they almost coincide with the upper bounds, but the ETS results never fall outside the MTR-MTS bounds.

In the bottom two panels of Figures 1.1 and 1.2 we add the MIV assumption. The bottom-left panels show the bounds using grandparent's schooling as a monotone instrumental variable and the bottom-right panels use the schooling of the spouse as a MIV.

Using the schooling of the grandparent as MIV gives bounds which are tighter than the MTR-MTS bounds. Both for mothers as for fathers the ETS results seem to fall outside the bounds for the highest and lowest levels of parents' schooling. The identifying power of the schooling of the spouse seems even stronger. Using spousal schooling as a MIV again reduces the bounds compared to the MTR-MTS bounds and now the point estimates fall outside the bounds for all levels of mother's schooling and for fathers this is true for the lowest and highest levels of schooling.

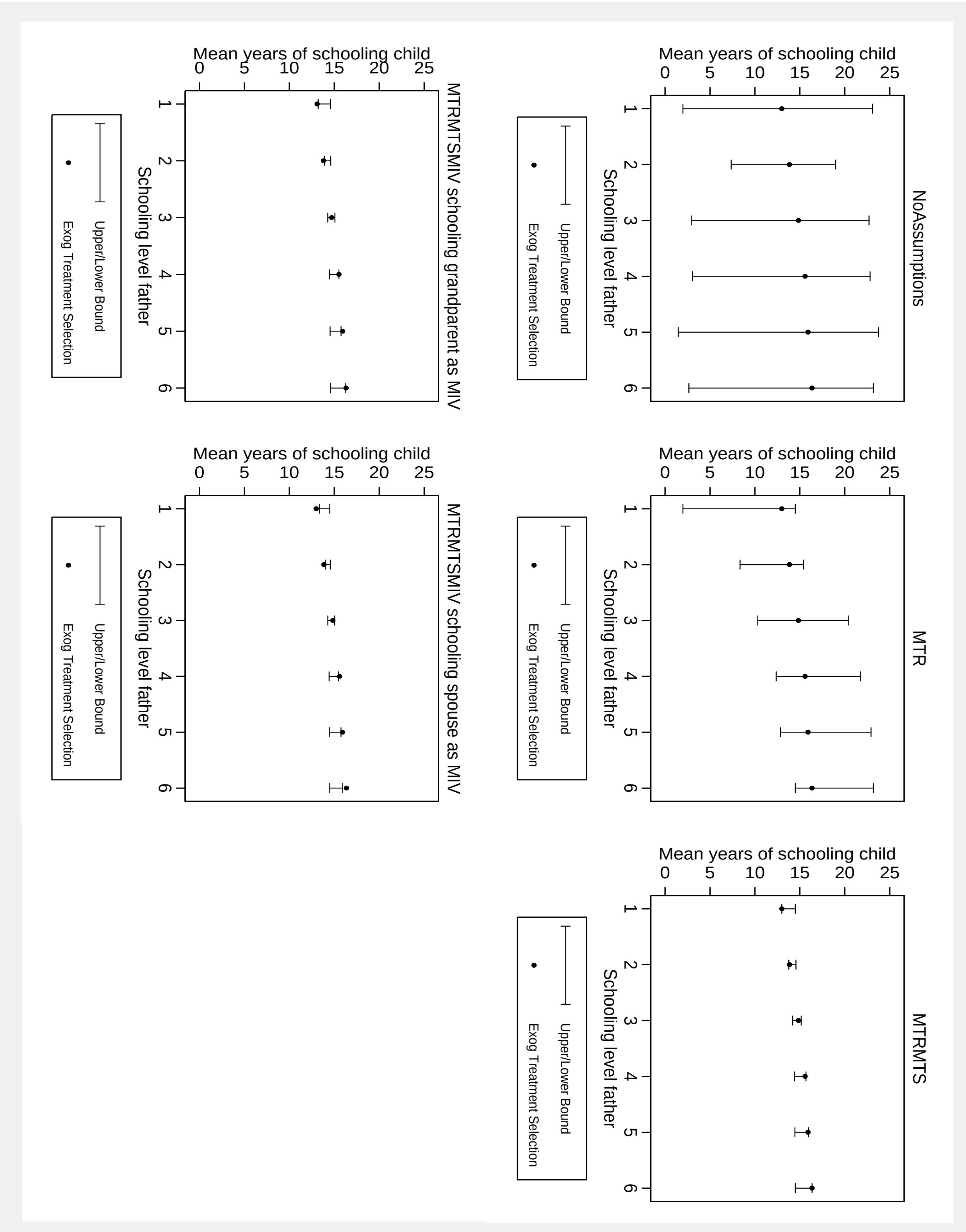
[8] For the no-assumption bounds and the MTR-bounds we take the lowest years of schooling of the child observed in the data (1 year) as $\underline{y}$ and the highest observed years (24 years) as $\overline{y}$.

Figure 1.1: Child's mean schooling as function of mother's schooling; nonparametric bounds compared to ETS



Schooling levels: 1: Less than high school, 2: High school, 3: Some college, 4: Bachelor's degree, 5: Master's degree, 6: More than a Master's degree. Sample using schooling grandparent as MIV is smaller (N=16912)

Figure 1.2: Child's mean schooling as function of father's schooling; nonparametric bounds compared to ETS



Schooling levels: 1: Less than high school, 2: High school, 3: Some college, 4: Bachelor's degree, 5: Master's degree, 6: More than a Master's degree. Sample using schooling grandparent as MIV is smaller (N=14614)

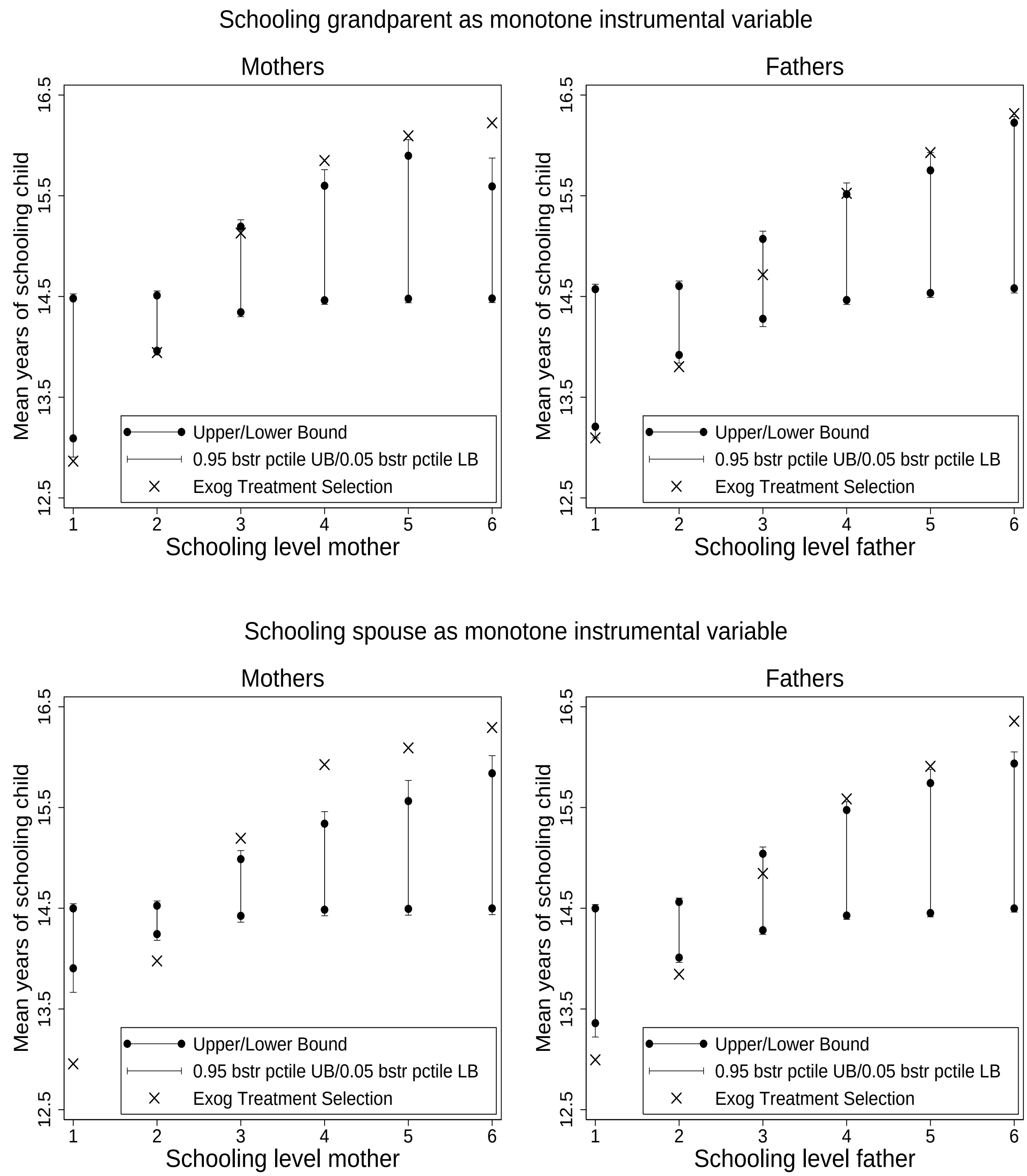
Figures 1.1 and 1.2 only show the bounds, to investigate whether the ETS results are significantly outside the bounds we will take a closer look at the MTR-MTS-MIV bounds in Figure 1.3 where we add 0.05 and 0.95 bootstrapped percentiles around the bounds.[9] Figure 1.3 shows that when we use grandparent's schooling as MIV, the ETS estimates of the effect of mother's schooling are significantly higher that the nonparametric upper bounds for schooling levels 4 (Bachelor's degree) and 6 (more than a Master's degree) and they are just outside the confidence intervals for levels 1 and 5. For fathers some of the ETS results are just outside the bootstrapped confidence intervals around the bounds but not as much as the results for mothers.

Figure 1.3 also shows that the identifying power of the schooling of the spouse as a monotone instrumental variable is indeed stronger than grandparent's schooling. For mothers all the ETS estimates fall outside the bootstrapped confidence intervals around the bounds. Also for fathers the ETS results for schooling levels 1, 2 and 6 are significantly outside the MTR-MTS-MIV bounds. ETS underestimates for low levels and overestimates for high levels of parents' schooling.

Up to now we have only looked at bounds on $E[y(t)]$ while we are interested in the effect of increasing parents' schooling from one level to the next. Table 1.3 shows bounds on $\Delta(s,t) = E[y(t)] - E[y(s)]$ for mother's level of schooling and Table 1.4 shows the results for father's level of schooling. The ETS results range from an increase of 0.17 years of schooling when increasing mother's schooling from a bachelor's degree to a master's degree ($\triangle\ (4,5)$), to an increase of 1.22 years when increasing mother's schooling from high school to some college ($\triangle\ (2,3)$). The ETS results on father's schooling seem to be more constant, although the results also vary, from 0.32 years for $\triangle\ (4,5)$ to 1 year for $\triangle\ (2,3)$. The no-assumption bounds and the MTR bounds are again not very informative, since they are relatively wide.

[9] Bootstrapped confidence intervals are based on 1000 replications. To control for the fact that there are multiple observations from one family, the sample obtained in each replication is a bootstrap sample of clusters.

Figure 1.3: MTR-MTS-MIV bounds compared to ETS–a closer look



The 0.05 and 0.95 bootstrap percentiles are based on 1000 replications. To adjust for the fact that the sample contains multiple children from one family the sample drawn during each replication is a bootstrap sample of clusters. Levels of schooling 1: Less than high school, 2: High school, 3: Some college, 4: Bachelor's degree, 5: Master's degree, 6: More than a Master's degree. Sample using schooling grandparent as MIV is smaller (N=16912 for mothers, N=14614 for fathers)

Table 1.3: Nonparametric bounds on the effect of mother's schooling on child's years of schooling

	ETS			No-assumption bounds			
	β	95% bstr. conf. int.		0.05 pctile	LB	UB	0.95 pctile
$\triangle(1,2)$	1.02	0.80	1.23	-14.62	-14.48	16.30	16.42
$\triangle(2,3)$	1.22	1.10	1.34	-14.57	-14.47	13.47	13.58
$\triangle(3,4)$	0.73	0.60	0.86	-19.75	-19.64	19.69	19.80
$\triangle(4,5)$	0.17	-0.07	0.41	-21.70	-21.63	20.88	20.98
$\triangle(5,6)$	0.20	-0.10	0.51	-22.46	-22.41	22.48	22.52
$\triangle(2,4)$	1.95	1.85	2.05	-14.86	-14.75	13.80	13.92

	MTR bounds				MTR-MTS bounds			
	0.05 pctile	LB	UB	0.95 pctile	0.05 pctile	LB	UB	0.95 pctile
$\triangle(1,2)$	0	0	13.47	13.51	0	0	1.58	1.76
$\triangle(2,3)$	0	0	11.61	11.67	0	0	1.40	1.48
$\triangle(3,4)$	0	0	10.76	10.81	0	0	1.59	1.67
$\triangle(4,5)$	0	0	9.86	9.90	0	0	1.61	1.81
$\triangle(5,6)$	0	0	9.72	9.76	0	0	1.80	1.98
$\triangle(2,4)$	0	0	13.01	13.12	0	0	2.00	2.08

	MTR-MTS-MIV bounds grandparent as MIV[a]				MTR-MTS-MIV bounds spouse as MIV			
	0.05 pctile	LB	UB	0.95 pctile	0.05 pctile	LB	UB	0.95 pctile
$\triangle(1,2)$	0	0	1.42	1.62	0	0	0.62	0.86
$\triangle(2,3)$	0	0	1.23	1.30	0	0	0.74	0.86
$\triangle(3,4)$	0	0	1.26	1.41	0	0	0.91	1.05
$\triangle(4,5)$	0	0	1.43	1.61	0	0	1.08	1.29
$\triangle(5,6)$	0	0	1.11	1.41	0	0	1.35	1.52
$\triangle(2,4)$	0	0	1.64	1.79	0	0	1.10	1.23

The 0.05 and 0.95 bootstrap percentiles are based on 1000 replications. To adjust for the fact that the sample contains multiple children from one family, the sample drawn during each replication is a bootstrap sample of clusters. 1: Less than high school, 2: High school , 3: Some college , 4: Bachelor's degree 5: Master's degree, 6: More than a Master's degree. [a]Sample using schooling grandparent as MIV is smaller (N=16912)

Table 1.4: Nonparametric bounds on the effect of father's schooling on child's years of schooling

	ETS			No-assumption bounds			
	β	95% bstr. conf. int.		0.05 pctile	LB	UB	0.95 pctile
$\triangle(1,2)$	0.85	0.71	0.99	-15.87	-15.73	16.98	17.10
$\triangle(2,3)$	1.00	0.88	1.11	-16.12	-16.00	15.34	15.47
$\triangle(3,4)$	0.74	0.61	0.87	-19.76	-19.64	19.85	19.95
$\triangle(4,5)$	0.32	0.12	0.54	-21.42	-21.34	20.67	20.79
$\triangle(5,6)$	0.45	0.25	0.66	-21.18	-21.09	21.70	21.77
$\triangle(2,4)$	1.74	1.63	1.84	-16.04	-15.92	15.46	15.58

	MTR bounds				MTR-MTS bounds			
	0.05 pctile	LB	UB	0.95 pctile	0.05 pctile	LB	UB	0.95 pctile
$\triangle(1,2)$	0	0	13.42	13.46	0	0	1.57	1.69
$\triangle(2,3)$	0	0	12.09	12.14	0	0	1.37	1.45
$\triangle(3,4)$	0	0	11.42	11.47	0	0	1.48	1.56
$\triangle(4,5)$	0	0	10.55	10.60	0	0	1.55	1.70
$\triangle(5,6)$	0	0	10.33	10.38	0	0	1.91	1.99
$\triangle(2,4)$	0	0	13.39	13.48	0	0	1.90	1.98

	MTR-MTS-MIV bounds grandparent as MIV[a]				MTR-MTS-MIV bounds spouse as MIV			
	0.05 pctile	LB	UB	0.95 pctile	0.05 pctile	LB	UB	0.95 pctile
$\triangle(1,2)$	0	0	1.40	1.50	0	0	1.20	1.35
$\triangle(2,3)$	0	0	1.15	1.26	0	0	1.03	1.11
$\triangle(3,4)$	0	0	1.24	1.37	0	0	1.19	1.28
$\triangle(4,5)$	0	0	1.29	1.46	0	0	1.32	1.45
$\triangle(5,6)$	0	0	1.69	1.75	0	0	1.48	1.60
$\triangle(2,4)$	0	0	1.60	1.73	0	0	1.46	1.56

The 0.05 and 0.95 bootstrap percentiles are based on 1000 replications. To adjust for the fact that the sample contains multiple children from one family, the sample drawn during each replication is a bootstrap sample of clusters. 1: Less than high school, 2: High school , 3: Some college, 4: Bachelor's degree 5: Master's degree , 6: More than a Master's degree.
[a]Sample using schooling grandparent as MIV is smaller (N=14614)

Adding the monotone treatment selection assumption tightens the bounds significantly. It gives bounds on the treatment effects ranging from an effect between 0 and 1.40 years when increasing mother's schooling from high school to some college, to an effect between 0 and 1.80 years when increasing mother's schooling from a master's degree to more than a master's degree. For the same increases in father's schooling the effects are respectively within [0, 1.37] years and within [0, 1.91] years. Still these bounds include a zero effect as well as an effect as large as the ETS results and are therefore not very instructive.

When we use grandparent's schooling as a monotone instrumental variable we get upper bounds that are lower than the MTR-MTS bounds, but they are still higher than the ETS results. Using the schooling of the spouse as a MIV gives bounds which are more informative. The ETS results on father's schooling are still within the bounds, but for the effect of increasing mother's schooling from high school to some college ($\triangle\ (2,3)$) the ETS result falls outside the bootstrapped confidence interval around the MTR-MTS-MIV bounds.

Increasing parents' schooling from high school to a bachelor's degree

Since most fathers and mothers either have a high school degree or a bachelor's degree we can, instead of looking at the effect of moving from one level of education to the next, investigate the effect of increasing mother's/father's schooling from a high school degree (12 years) to a bachelor's degree (16 years) ($\triangle\ (2,4)$). Table 1.3 shows that under the exogenous treatment selection assumption the effect of increasing mother's schooling from high school to a bachelor's degree increases child's schooling on average by 1.95 years. This ETS estimate falls within the no-assumption, MTR and MTR-MTS bounds. If we however use grandparent's schooling or the schooling of the spouse as MIV we obtain upper bounds which are significantly lower than 1.95. When we use grandparent's schooling as MIV we obtain an upper bound of 1.64, and when we use the schooling of the spouse as a monotone instrumental variable we obtain an upper bound of 1.10 years which is almost half the ETS estimate.

A similar pattern is observed when we look at the effect of increasing father's schooling from high school to a bachelor's degree in Table 1.4. The ETS estimate of this treatment effect is equal to 1.74 years. This is not significantly different from the upper bound using grandparent's schooling as MIV but it is significantly larger than the MTR-MTS-MIV upper bound of 1.46 years, when we use the schooling of the spouse as MIV.

Although the bounds do not exclude a zero effect of parents' schooling on years of schooling of the child, the upper bounds are informative since they are significantly smaller than the results obtained under the exogenous treatment selection assumption. These results are in line with the studies using twins, adoptees and some of the instrumental variables studies in the sense that most of these studies also find that OLS (ETS) overestimates the effect of parental schooling on child's schooling.

The effect of parents' schooling on the probability of a bachelor's degree

Instead of estimating the effect of parents' level of schooling on child's years of schooling we now focus on the effect on the probability that the child has a bachelor's degree ($\geq$16 years of schooling). Due to compulsory schooling laws most children finish high school. The most important difference in schooling outcomes between children is the difference between having completed college or not. Tables 1.6 and 1.7 therefore show the nonparametric bounds compared to the ETS estimates of the effect of parents' schooling on the probability that a child completes college.[10] The results are very similar to the results on years of schooling. The no-assumption and MTR bounds are again relatively wide. Table 1.5 shows that the MTR-MTS assumption is not rejected since the probability that the child has a bachelor's degree weakly increases with mother's and father's level of schooling. Adding the MTS assumption tightens the bounds and the bounds are narrowest when

[10] Since the probability of a bachelor's degree is between zero and one by definition, we take 0 as $\underline{y}$ and 1 as $\overline{y}$ when obtaining the no-assumption bounds and the MTR-bounds.

we add a MIV assumption, whereby the decline in the upper bound is strongest when we use the schooling of the spouse as a monotone instrumental variable.

Table 1.5: Probability that child has bachelor's degree by level of schooling mother/father

	Mothers		Fathers	
Schooling level parent	$E[P(y \geq 16yrs)\|z=u]^a$	P(z=u)	$E[P(y \geq 16yrs)\|z=u]^a$	P(z=u)
1: Less than high school (<12 years)	0.17	0.035	0.17	0.082
2: High school (12 years)	0.36	0.627	0.32	0.495
3: Some college (13-15 years)	0.58	0.158	0.52	0.142
4: Bachelor's degree (16 years)	0.75	0.131	0.70	0.141
5: Master's degree (17 years)	0.76	0.020	0.74	0.032
6: More than a Master's degree (>17 years)	0.79	0.028	0.81	0.107
N	*21,545*		*21,545*	

[a]MTR-MTS assumption not rejected

The ETS results indicate that increasing mother's schooling from a high school degree to a bachelor's degree ($\triangle(2,4)$) increases the probability that a child has a bachelor's degree with 40 percentage points which is very similar to the effect of father's schooling of 37 percentage points. These estimates are within the no-assumption, MTR and MTR-MTS bounds. Adding a MIV assumption gives a very different picture though, since the MTR-MTS-MIV upper bounds are notably smaller than the ETS estimates. Using grandparent's schooling as MIV gives an upper bound for mothers of 33 percentage points which is significantly smaller than the ETS estimate, and for fathers the upper bound is equal 34 percentage points. The MTR-MTS-MIV bounds using the schooling of the spouse as MIV give upper bounds which are even smaller; for mothers the effect is at most 22 percentage points and for fathers at most 31 percentage points. Both upper bounds are significantly different from the ETS estimates.

Table 1.6: Nonparametric bounds on effect of mother's schooling on child's probability of a bachelor's degree

	ETS			No-assumption bounds			
	β	95% bstr. conf. int.		0.05 pctile	LB	UB	0.95 pctile
$\triangle(1,2)^b$	0.19	0.15	0.23	-0.76	-0.75	0.59	0.60
$\triangle(2,3)$	0.23	0.20	0.25	-0.51	-0.50	0.71	0.72
$\triangle(3,4)$	0.17	0.14	0.20	-0.84	-0.83	0.88	0.88
$\triangle(4,5)$	0.01	-0.05	0.06	-0.96	-0.95	0.90	0.90
$\triangle(5,6)$	0.03	-0.03	0.09	-0.98	-0.97	0.98	0.98
$\triangle(2,4)$	0.40	0.38	0.42	-0.50	-0.50	0.74	0.75

	MTR bounds				MTR-MTS bounds			
	0.05 pctile	LB	UB	0.95 pctile	0.05 pctile	LB	UB	0.95 pctile
$\triangle(1,2)$	0	0	0.48	0.49	0	0	0.30	0.33
$\triangle(2,3)$	0	0	0.66	0.67	0	0	0.26	0.28
$\triangle(3,4)$	0	0	0.64	0.64	0	0	0.33	0.35
$\triangle(4,5)$	0	0	0.57	0.58	0	0	0.30	0.35
$\triangle(5,6)$	0	0	0.56	0.57	0	0	0.33	0.37
$\triangle(2,4)$	0	0	0.73	0.74	0	0	0.41	0.42

	MTR-MTS-MIV bounds grandparent as MIV[a]				MTR-MTS-MIV bounds spouse as MIV			
	0.05 pctile	LB	UB	0.95 pctile	0.05 pctile	LB	UB	0.95 pctile
$\triangle(1,2)$	0	0	0.27	0.30	0	0	0.12	0.19
$\triangle(2,3)$	0	0	0.23	0.25	0	0	0.13	0.15
$\triangle(3,4)$	0	0	0.26	0.30	0	0	0.19	0.22
$\triangle(4,5)$	0	0	0.24	0.29	0	0	0.17	0.23
$\triangle(5,6)$	0	0	0.19	0.26	0	0	0.26	0.29
$\triangle(2,4)$	0	0	0.33	0.37	0	0	0.22	0.25

The 0.05 and 0.95 bootstrap percentiles are based on 1000 replications. To adjust for the fact that the sample contains multiple children from one family,the sample drawn during each replication is a bootstrap sample of clusters. 1: Less than high school, 2: High school, 3: Some college, 4: Bachelor's degree 5: Master's degree , 6: More than a Master's degree.
[a]Sample using schooling grandparent as MIV is smaller (N=16912)

Table 1.7: Nonparametric bounds on effect of father's schooling on child's probability of a bachelor's degree

	ETS			No-assumption bounds			
	β	95% bstr. conf. int.		0.05 pctile	LB	UB	0.95 pctile
$\triangle(1,2)$	0.15	0.12	0.17	-0.78	-0.77	0.65	0.66
$\triangle(2,3)$	0.20	0.17	0.23	-0.60	-0.59	0.77	0.78
$\triangle(3,4)$	0.17	0.14	0.20	-0.84	-0.83	0.88	0.89
$\triangle(4,5)$	0.04	-0.00	0.09	-0.94	-0.93	0.89	0.90
$\triangle(5,6)$	0.07	0.03	0.12	-0.91	-0.90	0.96	0.96
$\triangle(2,4)$	0.37	0.35	0.40	-0.57	-0.57	0.80	0.80

	MTR bounds				MTR-MTS bounds			
	0.05 pctile	LB	UB	0.95 pctile	0.05 pctile	LB	UB	0.95 pctile
$\triangle(1,2)$	0	0	0.51	0.52	0	0	0.30	0.32
$\triangle(2,3)$	0	0	0.69	0.69	0	0	0.28	0.29
$\triangle(3,4)$	0	0	0.68	0.69	0	0	0.32	0.33
$\triangle(4,5)$	0	0	0.63	0.63	0	0	0.31	0.34
$\triangle(5,6)$	0	0	0.61	0.62	0	0	0.36	0.38
$\triangle(2,4)$	0	0	0.76	0.76	0	0	0.40	0.42

	MTR-MTS-MIV bounds grandparent as MIV[a]				MTR-MTS-MIV bounds spouse as MIV			
	0.05 pctile	LB	UB	0.95 pctile	0.05 pctile	LB	UB	0.95 pctile
$\triangle(1,2)$	0	0	0.26	0.29	0	0	0.24	0.27
$\triangle(2,3)$	0	0	0.23	0.25	0	0	0.21	0.22
$\triangle(3,4)$	0	0	0.27	0.29	0	0	0.26	0.28
$\triangle(4,5)$	0	0	0.25	0.29	0	0	0.26	0.30
$\triangle(5,6)$	0	0	0.31	0.33	0	0	0.30	0.32
$\triangle(2,4)$	0	0	0.34	0.36	0	0	0.31	0.34

The 0.05 and 0.95 bootstrap percentiles are based on 1000 replications. To adjust for the fact that the sample contains multiple children from one family, the sample drawn during each replication is a bootstrap sample of clusters. 1: Less than high school, 2: High school , 3: Some college, 4: Bachelor's degree 5: Master's degree , 6: More than a Master's degree.[a]Sample using schooling grandparent as MIV is smaller (N=14614)

Figure 1.4: Bounds on the effect of increasing parents' schooling from high school to a bachelor's degree

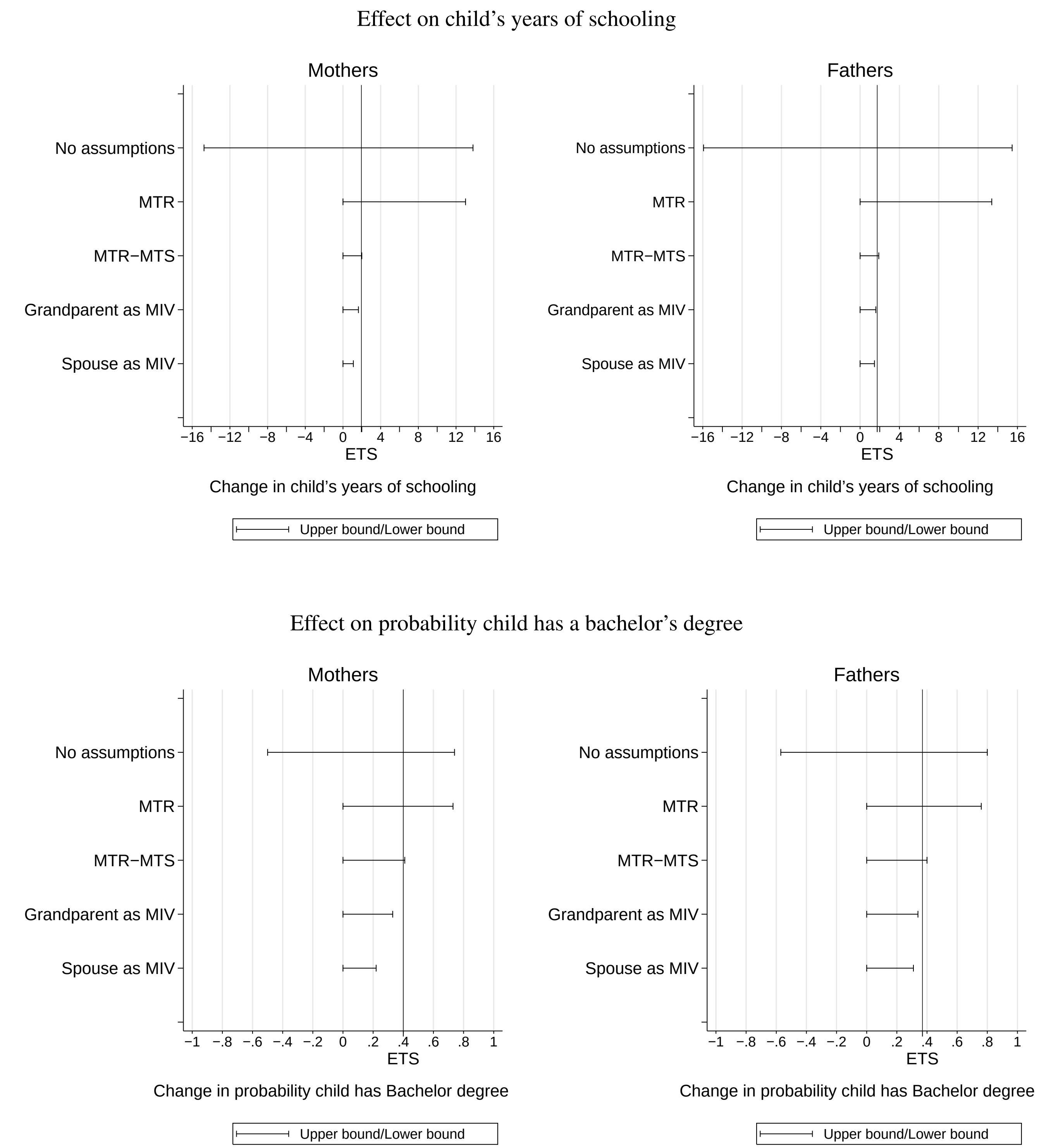


Figure 1.4 shows the bounds on the treatment effects of increasing mother's (father's) schooling from a high school degree to a bachelor's degree on child's years of schooling (top panel) and on the probability that the child has a bachelor's degree (bottom panel). These pictures clearly show how the bounds are tightened by adding the MTR, MTS and MIV assumptions. Both for the effect on years of schooling as the for effect on the probability of a bachelor's degree the ETS results clearly overestimate the effect of parents' schooling compared to the MTR-MTS-MIV upper bounds. This effect is strongest for mothers, since here the upper bounds (using the schooling of the spouse as MIV) are almost half the ETS results.

1.5 Conclusion

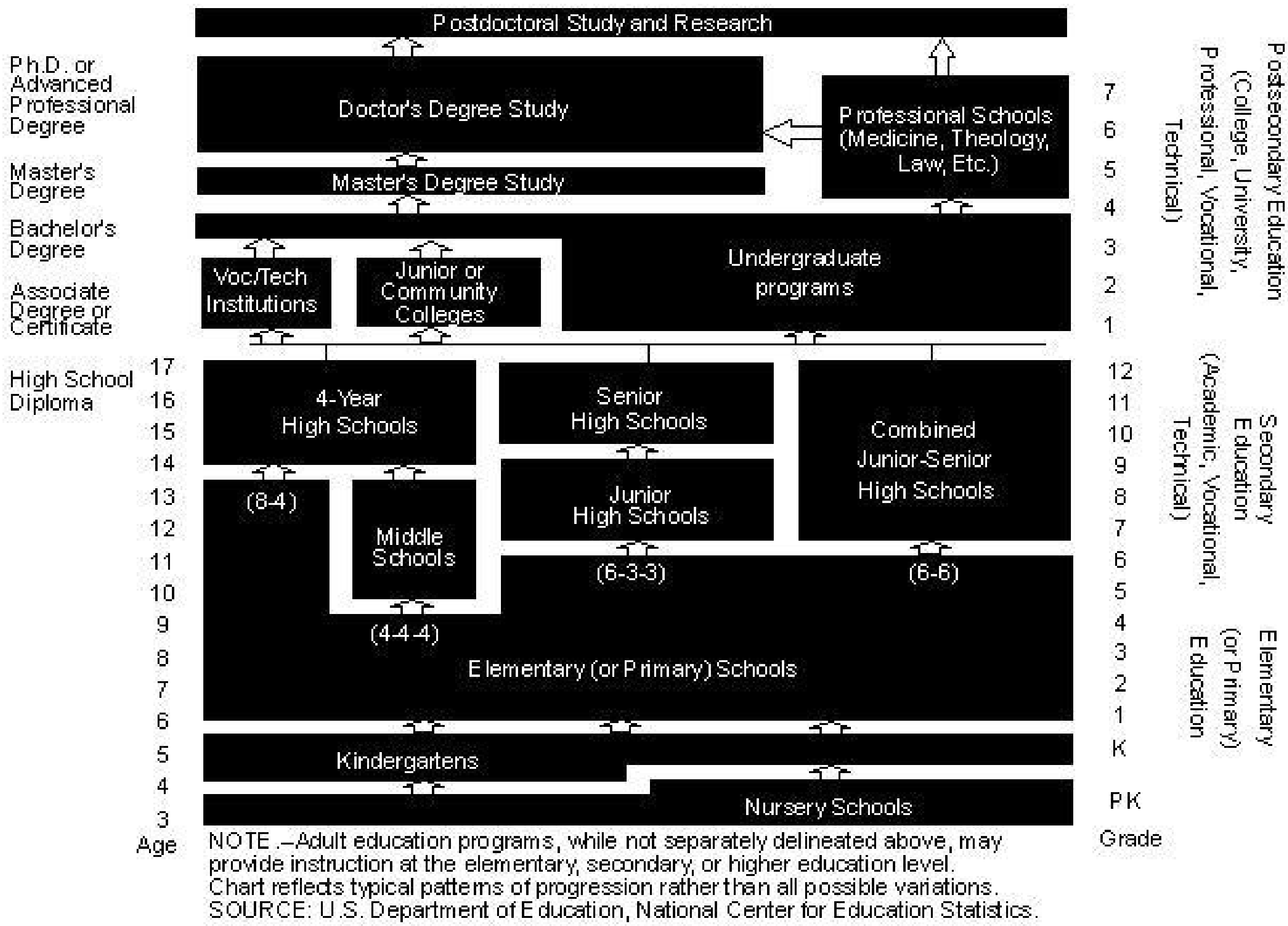
Regressing child's schooling on parents' schooling generally gives large positive and significant estimates. Since these estimates need not be equal to the true causal relation, different identification strategies have been used. These identification approaches generally put strong requirements on the data since you need a large data set with completed schooling outcomes of both parents and their children and you either need a large sample of twins or adoptees or a good instrument. And even if you are able to apply any of these identification strategies, you will always have to make a number of assumptions in order to interpret the results as causal.

This chapter used a relatively new approach to learn more about the effect of father's and mother's schooling on the schooling of their child. By making relatively weak and testable assumptions we have obtained bounds on the effect of increasing parents' schooling on years of schooling of the child and on the probability that the child obtains a bachelor's degree. We started with obtaining bounds without making any assumptions and then tightened the bounds by subsequently adding a monotone treatment response assumption (MTR), a monotone treatment selection assumption (MTS) and a monotone instrumental variable assumption (MIV), whereby we used the schooling of the grandparent and the schooling of the spouse as monotone instrumental variables.

Although the bounds on the treatment effects include a zero effect, the upper bounds are informative especially for the effect of increasing parents' schooling from a high school degree to a bachelor's degree. For mothers the MTR-MTS-MIV upper bounds are almost half the estimates under the exogenous treatment selection assumption. Also for the effect of increasing father's schooling from high school to a bachelor's degree the estimates under the exogenous treatment selection assumption are significantly larger than the MTR-MTS-MIV upper bounds. The results in this chapter show that the effect of parents' schooling is lower than what one would conclude on the basis of simple correlations and that there might even be no effect at all. These findings are in line with the studies using twins, adoptees and some of the instrumental variables studies in the sense that most of these studies also find that OLS (ETS) overestimates the effect of parental schooling on child's schooling.

Appendix

Figure 1.5: Map of the U.S. Education System



(http://www.ed.gov/about/offices/list/ous/international/usnei/us/edlite-map.html)