Working Paper No. 96

Does Private Tutoring Work?
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Leading House Working Paper No. 96

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January 2014

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Abstract

Private tutoring has become popular all over the world. However, the evidence on the effect of private tutoring is inconclusive, therefore, this paper attempts to improve the existing literature by using nonparametric bounds methods to find out if private tutoring yields any substantial returns for the individual. The present examination uses a large representative dataset to identify bounds, first, without imposing assumptions and second, it applies weak nonparametric assumptions to tighten the bounds. Under relatively weak assumptions, I find some evidence that private tutoring improves students' academic outcome in reading. However, the results indicate a heterogeneous and nonlinear effect of private tutoring.

1 Introduction

Private tutoring – fee-based tutoring in academic subjects which is additional to the provision by formal schooling - has become popular all over the world (Baker & LeTendre, 2005; Bray, 1999, 2011; Dang & Rogers, 2008; Jung & Lee, 2010; Mariotta & Nicoli, 2005; Southgate, 2009). Despite the widespread nature of private tutoring to date there is little quantitative research on the impact of private tutoring on students' academic performance.

Assessing the impact of privately paid tutoring faces fundamental identification problems. It is well known that educational expenditures on a student are not exogenous. Therefore participation in private tutoring is endogenous and correlated with at least some unobservable personal and family characteristics. A difficulty is that one cannot observe the outcomes a person would experience under all treatments. At most one can observe the outcome that a person experiences under the treatment he or she actually receives. Dealing with these difficulties, recent literature shows mixed results. Most of the studies find positive effects of private tutoring on students' academic outcome, for example in a randomized experiment in India (Banerjee, Cole, Duflo, & Linden, 2007), in a meta-analysis of randomized trials (Ritter, Barnett, Denny, & Albin, 2009), with an instrument-variable (IV) approach in Japan (Ono, 2007), a regression-discontinuity (RD) approach in the US (Jacob & Lefgren, 2004) or a combination of both approaches in Israel (Lavy & Schlosser, 2005). But no effect is found applying an IV approach in Indonesia (Suryadarma, Suryahadi, Sumarto, & Rogers, 2006). Different explanations might explain these diverging results. One potential cause is that the findings show different local average treatment effects (LATE) and not an average treatment effect (ATE). The measured LATE of private tutoring equals the ATE only if the effect of the tutoring is linear and homogenous. Another potential cause for the diverging results might be that the assumptions made do not hold, but lead to an invalid estimate.

Hence, the credibility of empirical analysis depends on the strength of the underlying assumptions. Therefore this study applies a nonparametric bounds method, introduced by Manski (1990, 1997) and developed by Manski and Pepper (2000, 2009), to calculate lower and upper bounds of the treatment effect with as few assumptions as possible. This bounds method has been applied, for example, in different recent studies (Blundell, Gosling, Ichimura, & Meghir, 2007; Boes, 2010; Gerfin & Schellhorn, 2006; Gundersen, Kreider, & Pepper, 2012; Haan, 2011; Kang, 2011; Kreider, Pepper, Gundersen, &

Jolliffe, 2012; Manski & Pepper, 2011; Pinkovskiy, 2013). Even though this approach produces a range instead of a point estimate, the bounds are informative because the true causal effect of private tutoring is somewhere between these estimated bounds. However, these bounds on the average treatment effect of private tutoring are an important step towards identifying the causal effect of private tutoring on students' academic achievement. There exists no study, though, that applies this method to identify the causal impact of private tutoring on students' achievement. Using a representative dataset of the Swiss PISA 2009 cohort this paper analyses the question whether participation in private tutoring lessons has a causal effect on students' academic achievement in mathematics and reading.

The partial identification approach developed in this research allows evaluating bounds on the ATE of private tutoring under different assumptions, which allows one to successively layering stronger identification assumptions and therefore making transparent how assumptions shape inferences about the causal effect of private tutoring. The analysis starts with investigating the effect of private tutoring without imposing assumptions. Then the analysis imposes weak nonparametric assumptions to tighten the bounds, first, it assumes monotone treatment selection (MTS) assumption that states that attending private tutoring classes is weakly monotonically related with poor academic outcome. Second, I use the parents' education as a monotone instrument variable (MIV). Third, this study applies monotone treatment response (MTR) that means the effect of private tutoring to be not negative.

The tightest bounds show a positive causal impact of private tutoring lessons in the intermediate school track on students' academic achievement in reading. Although these results suggest that private tutoring leads to a better outcome, I cannot reject the hypothesis that private tutoring is ineffective. However, the results suggest a heterogeneous and nonlinear effect.

This paper is structured as follows. Section 2 describes the Swiss education system with special focus on private tutoring and the data. Section 3 explains the identification problem and the nonparametric bounds method. Section 4 shows the results. Section 5 concludes.

2 Swiss Education System and Data

2.1 Swiss Education System

Compulsory school in Switzerland comprises nine years of schooling: around five to six years of primary school and three to four years of lower secondary school. At the lower secondary school level, different school type models exist that vary from canton to canton[1]. The majority of school type models sorts pupils into different school tracks according to their intellectual abilities. Although two to four different tracks exist, the majority of cantons apply a three track model: an upper-level school track (Progymnasium), which teaches the more intellectually demanding courses; an intermediate level school track (Sekundarschule), and finally one offering basic-level courses (Realschule).

After finishing the compulsory school (9th grade), students can choose among two different possibilities: Full-time educational school (Gymnasium or Fachmittelschule) or vocational track (apprenticeship training). In Switzerland, about 20 per cent of school leavers attend a Baccalaureate school (Gymnasium), which prepares for university. About 60 per cent of school leavers choose apprenticeship training. This so called "dual-education" provides them with formal and on-the-job training within a training firm, and one to two days per week of formal schooling in a vocational school.

2.2 Private Tutoring in Switzerland

Private tutoring in Switzerland is completely unregulated and takes mainly two different forms. The first type and the lion's share is one-to-one instruction by a privately-paid teacher either at the teacher's or at the student's home (ident.). The second type of private tutoring is undertaken by profit-oriented school-like organizations where professional teachers or students tutor in a classroom setting (for example ´Kick Lernstudio´ or ´Studienkreis´). Such centres usually own or rent multi-story buildings in the city centres. Students attend these centres additional to the formal school hours. These centres provide smaller class sizes (private, in groups of two or sometimes up to 10 students), special materials, e.g. workbooks, and improved student-teacher relations compared to the formal schools.

Research about the extent of private tutoring in Switzerland is rare. Analysing TIMSS (Trends in International Mathematics and Science Study) data from 1995 Baker and

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[1]The equivalent of states in the US.

LeTendre (2005) show a weekly participation rate of 25% for the 8th graders. A study for the canton Tessin using PISA 2003 data finds a participation rate of 15% for the 9th graders (Mariotta, 2006).

2.3 Data

This study uses data from the Program for International Student Assessment (PISA) 2009 conducted by the Organization for Economic Cooperation and Development (OECD). Since 2000, PISA measures every three years the performance of 15-year-old students at the end of compulsory schooling. Performance in mathematics, science and reading are investigated; PISA 2009 focused on reading (OECD, 2011a).

The PISA survey follows a two-stage sampling process: First, schools are sampled and then students are sampled in the participating schools. In a simple random sample of schools every school has the same selection probability and within the selected schools the student selection probability will vary according to the school size, because in reality schools differ in size. Therefore in a small school, the student selection probability will be larger than in a large school. To avoid these unequal selection probabilities for pupils, the schools' probability to be selected are weighted with their size (OECD, 2009).

The PISA 2009 data collection for Switzerland includes a large nationally representative sample of 15-year old students and a supplementary study of grade-9 students from a selection of cantons. These surveys include a national option on the demand of private tutoring. These questions provide information about the frequencies, motives, teachers etc. of private tutoring demand in the 8/9th grade among the 9th graders. The analysis in this paper makes use of the national 9th grade survey with 13'472[2] students.

The nationwide representative PISA 2009 dataset shows a participation rate in private tutoring of 30% for Switzerland (ident.) for 9th grade students, with around one fifth of all students attending private tutoring classes every week and for several years. Girls and students with richer and more educated parents are significantly more often sent to private tutoring lessons.

The main outcome variable is students' academic achievement. Academic achievement is measured with the PISA 2009 scores of Swiss 9th graders in mathematics and reading. To tighten the nonparametric bounds an instrument variable approach is applied where parents schooling (IV) serves as monotone instrument variable. This will be explained in

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[2] Due to item non-response 2383 observations were deleted.

more detail in the next section. Table 1 shows the descriptive statistics for students without any private tutoring and with private tutoring in reading and mathematics.

[Table 1 near here]

3 Partial Identification Strategy

I consider the problem of learning the effect of private tutoring on students' academic achievement (in mathematics and reading). The analysis wants to identify the average treatment effect (ATE) of going to private tutoring classes on students' achievement, that is,

$$ATE_{r,m} (1,0) = E[y(1)|x] – E[y(0)|x] \quad\quad\quad\quad [1]$$

Where y is student's academic achievement in PISA and $y(1)^3$ denotes a student's outcome if attending private tutoring classes and y(0) if not. For each student there are two potential outcomes, y(1) and y(0). The Average Treatment Effect (ATE) represents the causal effect of tutoring on achievement and is calculated by the mean outcome if all students would receive private tutoring (y(1)) versus the mean outcome if all students would not attend private tutoring (y(0)), see equation [1].

Under the assumption of exogenous treatment selection (ETS) the ATE is point estimated. ETS assumes that E[y(1)|z=0] = E[y(1)|z=1] and E[y(0)|z=0] = E[y(0)|z=1] and therefore (Beresteaunu & Manski, 2000) the ATE = E[y(1)|z=0] - E[y(0)|z=1] = E[y|z=1] - E[y|z=0]. In particular, z=1 indicates that the pupil truly received the treatment and z=0 otherwise.

For each student we do not observe one of the two potential outcome z=0 (e.g. what a student's academic achievement would have been if he had not attended private tutoring lessons) and therefore this approach leads to biased results because students who take private tutoring may differ in various unobserved variables from those who do not. This is referred to as the selection problem.

Instead of imposing assumptions that lead to a point estimate this analysis applies the nonparametric bounds method (Manski & Pepper, 2009; Manski, 1990, 2007) and imposes as little assumptions as possible to calculate a lower and an upper bound of the

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[3] To make the notation more compact we leave the conditioning on covariates (x) and the notation for mathematics (m) and reading (r) implicit in the following.

private tutoring effect. The true causal effect of the treatment lies somewhere between the lower and the upper bound. These bounds lead to partial conclusions.[4]

For these bounds I define the outcome (y) as the PISA test score of a student in mathematics or reading and t as the treatment indicator. $z \, \varepsilon \, T$ denotes as well the treatment received by person. $z=1$ denotes that a student participated in private tutoring in the 8 and/or 9th grade in mathematics or reading and $z=0$ otherwise. The response function $y(.) : T \rightarrow Y$ maps the treatments $t \, \varepsilon \, T$ into outcomes $y(t) \, \varepsilon \, Y$. $y(t)(t=z)$ is the realized outcome and $y(t)(t \neq z)$ is the counterfactual. The outcome space Y has in general bounds $-\infty < K_0 < K_1 < +\infty$ and when specified greatest lower bound $K_0 \equiv \inf Y$ and least upper bound $K_1 \equiv \sup Y$. Using the Law of Iterated Expectations and following Manski and Pepper (Manski & Pepper, 2011; Manski, 2007) I decompose

$$E[y(1)] = E[y(1)|z=1] \, P(z=1) + E[y(1)|z=0] \, P(z=0) \tag{2}$$

where $P(z=1)$ or $P(z=0)$ are the probabilities of receiving or not receiving the treatment.

3.1 Worst-case Bounds for Average Treatment Effects

Manski (1990) shows that is possible to identify bounds by adding very weak assumptions. I am, though, not able to identify the unobservable counterfactual (latent outcome) $E[y(1)|z=0]$ or $E[y(0)|z=1]$ from my data without imposing very strong and probably incredible assumptions. Therefore, this analysis replaces the unobserved by its bounds and these are for each treatment t, the worst-case bounds (no-assumptions bounds following (Manski, 1990)) with the very weak assumptions of a bounded output y(t) and stable unit treatment value. This yields to the following sharp bounds for y(t) in the binary treatment case of private tutoring:

$$E[y(1)|z=1] \, P(z=1) + K_0 * P(z=0) \leq E[y(1)] \leq E[y(1)|z=1] \, P(z=1) + K_1 * P(z=0) \tag{3}$$

$$E[y(0)|z=0] \, P(z=0) + K_0 * P(z=1) \leq E[y(0)] \leq E[y(0)|z=0] \, P(z=0) + K_1 * P(z=1)$$

And the resulting bound on the ATE[5] is

$$E[y(1)|z=1] \, P(z=1) + K_0 * P(z=0) - [E[y(0)|z=0] \, P(z=0) + K_1 * P(z=1)] \tag{4}$$
$$\leq E[y(1)] - E[y(0)] \leq$$
$$E[y(1)|z=1] \, P(z=1) + K_1 * P(z=0) - [E[y(0)|z=0] \, P(z=0) + K_0 * P(z=1)]$$

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[4] It is important to notice, that these bounds are not confidence intervals. They express the ambiguity created by the selection problem (Manski & Pepper, 2011).

[5] The ATE $(E[y(1)] - E[y(0)])$ is calculated as follows: The lower bound on $E[y(1)]$ minus the upper bound on $E[y(0)]$ is the lower bound of the average treatment effect. The upper bound on $E[y(1)]$ minus the lower bound on $E[y(0)]$ is the upper bound of the ATE.

The two illustrations on the left in Figure 1 show the upper and lower bounds for $E[y(1)]$ and $E[y(0)]$ without assumptions. These worst-case bounds[6] are often too wide to be useful. In order to get narrower bounds, a few assumptions can be invoked. The analysis will subsequently add the monotone treatment selection assumption, monotone instrument variable and the monotone treatment response assumption.

[Figure 1 near here]

3.2 Monotone Treatment Selection (MTS)

The first assumption introduced in the analysis is monotone treatment selection (MTS) supposing that sorting into treatment is not exogenous but monotone in the sense that the counterfactual outcome is smaller for those students who participated in private tutoring $(z=1)$ than for those who did not participate $(z=0)$. In other words, students who participated in private tutoring have a higher probability (because of observed and unobserved characteristics) of being a bad achiever than those who did not participate in private tutoring would have if they had participated in private tutoring.[7] Therefore I assume a negative self-selection with $E[y(1)|z=1] \leq E[y(1)|z=0]$ and $E[y(0)|z=1] \leq E[y(0)|z=0]$.

This assumption implies that if all students would receive private tutoring students actually receiving tutoring lessons would on average still perform worse than students actually without private tutoring. The two illustrations on the right in Figure 1 show how the MTS assumption can tighten the bounds. One observes the mean achievement for students that did not attend private tutoring lessons. Under MTS assumptions this achievement will not be lower than the mean achievement for students actually going to private tutoring lessons. Hence, the mean realized students' achievement for students with private tutoring is the lower bound, indicating that students with treatment could not have done any better in the control state than those observed in the control group. MTS yields a lower bound for the counterfactual $E[y(1)|z=0]$ which is $E[y(1)|z=1]$, because for

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[6]Manski bounds are sharp bounds, i.e. nothing else can be learned in face of the censored data. Proof in (Heckman & Leamer, 2007; Heckman & Vytlacil, 2000; Manski, 2007).
[7] It could be that ability and taste for private tutoring may be positively associated. Therefore, more able students want to go to further lessons after school. But I am sure, that even if my assumption does not warrant unquestioned acceptance, it certainly is plausible.

each z<t it must be true that $E[y(t)]$ is at most as large as $E[y|z=t]$, and an upper bound for $E[y(0)|z=1]$ which is $E[y(0)|z=0]$. In the binary case the bounds under MTS are:

$$E[y|z=1]\leq E[y(1)] \leq E[y(1)|z=1] \, P(z=1) + K_1 * P(z=0) \tag{5}$$

$$E[y(0)|z=0] \, P(z=0)+ K_0 * P(z=1) \leq E[y(0)] \leq E[y|z=0] \tag{6}$$

3.3 Monotone Instrument Variable (MIV)

A second assumption to tighten the bounds is the presence of an instrument variable (IV). This analysis will use the parents' education v as a monotone instrument variable. With this additional variable v, it is possible to create sub-samples for each value of v and then to obtain bounds on the mean potential outcomes within each of these sub-samples (Manski & Pepper, 2000).

This approach applies the traditional IV[8] but loosens the assumptions with mean monotonicity (MIV)[9] (Manski & Pepper, 2000):

$$u_1 \leq u \leq u_2 \rightarrow E[y(t)|v=u_1] \leq E[y(t)|v=u] \leq E[y(t)|v=u_2] \tag{7}$$

In contrast to an instrumental variable assumption with mean independence, the monotone instrumental variable assumption allows a weakly monotone positive relationship between v and the mean potential outcome (Manski & Pepper, 2000). By using the parents' education as an MIV, I assume that the mean schooling function of the pupil is monotonically increasing in the parents' education.[10] This innocuous MIV assumption allows for a direct impact of the parents education on students' academic achievement as long as the effect is not negative. The choice of the instrument is based on research on intergenerational mobility which shows that educational achievement is positively correlated with the parents' education (Björklund & Salvanes, 2011; Black & Devereux, 2011).

The MIV bounds are (similar for $E[y(0)]$[11]:

$$\sum_{u\epsilon V} P(v=u) \, \{\sup_{u_1 \leq u} [E(y| \, v= u_1, z=1) \, P(z=1| \, v= u_1) + K_0*P(z=0| \, v= u_1)]\}$$

$$\leq E[y(1)] \leq \tag{8}$$

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[8]For example Ono (2007) uses tutoring during secondary education as in IV to measure the effect of tutoring in tertiary education.

[9] The identifying power of an MIV is examined in (Manski & Pepper, 2000).

[10]The MIV used is discrete and takes four possible values: No post-obligatory education, vocational education, secondary academic education, tertiary education.

[11] Proof see Manski and Pepper (2000).

$$\sum_{u \varepsilon V} P(v=u) \{ \inf_{u2 \geq u} [E(y| v= u_2, z=1) P(z=1| v= u_2) + K_1 * P(z=0| v= u_2)] \}$$

From Equation [7] and [8] follows that for the sub-sample $v = u$ there is a new lower bound which is the largest lower bound over all sup-samples $v \leq u$. The new upper bound is the smallest upper bound over all sub-samples $v \geq u$. To calculate these bounds the analyses divides the sample into four groups of parents' education and uses the average estimates of MTS or MTS-MTR bounds to get the MTS-MIV or MTS-MTR-MIV bounds.

3.4 Monotone Treatment Response (MTR)

The third assumption employed is the monotone treatment response (MTR) (Manski, 1997). MTR states, ceteris paribus, that the outcome is a weakly increasing function of the treatment, such that $\delta \geq 0$ for every student. The assumption implies that there exist no negative impacts of private tutoring on students' academic performance. This assumption is strong but fostered by the recent literature presented and therefore plausible. It is hard to imagine, that parents sent their children to private tutoring classes when there is a negative impact on students' academic achievement.

Even though this evidence, potential negative effects of private tutoring on students' academic outcome could arise if private tutoring crowds out students' self-learning time or students' attention in class. Lee (2013) shows that private tutoring positively affects low-achieving students on their attention to school lessons and has no effect for middle- and upper-achieving students. To control for a possible crowding out effect on students self-learning time I make use of the PISA 2006 questions about tutoring out-of-school and self-learning time.[12] Comparing self-learning time for students with and without tutoring (see Appendix) shows a significant positive effect of tutoring on students' self-learning time in reading and mathematics, indicating that no crowding out effect exists. These results are robust for all levels (zero up to six and more hours per week) of self-learning time. However MTR is a controversial assumption and I will therefore show the results for the applied assumptions separately.

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[12] Self-learning time was not questioned in PISA 2009. For this present research the questions in the international PISA student questionnaire concerning tutoring are not detailed enough to distinguish between private (and privately-paid) tutoring and other out-of-school time lessons. Comparing participation rates in tutoring (international question) and private tutoring (national option on privately-paid tutoring) shows an over estimation in the international question. The international question leads to participation rates of 40% (OECD, 2011b) in tutoring compared to 30% participation rate in privately-paid tutoring.

MTR allows estimating whether there exists a positive effect of private tutoring or whether there is no effect at all. MTR assumes that treatments are ordered and y(.) is monotone in the treatment and therefore observations of the realized outcome y can be informative about the counterfactual outcomes y(t), $t \neq z$ (Manski, 2007). MTR for $E[y(1)]$ is specified as follows, when private tutoring is assumed to weakly increase students' performance:

$$E[y(1)|z=0] \geq E[y(0)|z=0]$$

$$E[y(1)|z=1] \geq E[y(0)|z=1] \tag{9}$$

The two illustrations in the middle of Figure 1 show how the MTR assumption can be used to tighten the bounds around the two potential outcomes. The data provide information on the mean outcome of students without private tutoring. Under MTR assumption for students without private tutoring their observed mean outcome will not be lower than to what their mean outcome would have been if they had attended private tutoring classes. Therefore, the observed mean outcome for these students without private tutoring $E[y|z=0]$ can be used to tighten the lower bound for students with z=0. For the students with private tutoring, under MTR assumption, the potential outcome will not be higher than the mean outcome we observe. $E[y|z=1]$ can therefore be used as an upper bound for the students with z=1.

In the case of a binary treatment (private tutoring or not) the bounds under MTR can be expressed by:

$$E[y] \leq E[y(1)] \leq E[y|z=1] \, P(z=1) + K_1*P(z=0) \tag{10}$$

$$E[y|z=0] \, P(z=0) + K_0*P(z=1) \leq E[y(0)] \leq E[y] \tag{11}$$

If I impose MTR as well as MTS the lower bound for $E[y(1)]$ is the higher lower bound of MTR and MTS. The upper bound on $E[y(0)]$ is the lower bound of MTR and MTS.

4 Results

Assuming exogenous treatment selection (ETS) shows a negative impact (ATE) of private tutoring on students' academic achievement (Figure 3a and 3b).With our data at hand, there might be a self-selection of bad performing students into private tutoring explaining the negative relationship between private tutoring on student performance.

Figure 2 shows the worst-case nonparametric bounds on students' academic achievement in reading (Figure 2a) and mathematics (Figure 2b) as a function of attending private tutoring lessons or not. Logically – because of the PISA definition – the PISA results of students can never be lower than 0 points and never higher than 1000 points.[13] Realized PISA points 2009 for reading and mathematics lie between the interval 120 and 860. Thus, the absolute worst-case bounds indicate the ATE for reading must be in the interval [-394, 346]. ATE for mathematics for the absolute worst-case bounds lies in the interval [-422, 318]. Using the actual maximum and minimum points (WC max) in PISA 2009 for reading (124, 771) and mathematics (125, 856) the bounds shrink a little bit and the ATE for test reading must be in the interval [-382, 265] and for mathematics in [-417, 312]. In Swiss PISA 2009 95% of the students scored in reading in the interval [347, 675] and in mathematics in the interval [369, 721]. Thus, using these 95 per cent minimum and maximum to calculate the upper and lower worst-case bounds, the ATE for reading is in the interval [-171, 157] and for mathematics must be in the interval [-184, 168]. Applying the very weak assumption that the students will score somewhere in between where 95 per cent of all students do allows us to reduce the interval for the ATE significantly.[14] However, without additional assumptions about the selection, I cannot eliminate the possibility that private tutoring has a positive or negative effect on students' academic achievement.

[Figure 2a near here]

[Figure 2b near here]

Self-selection into private tutoring is a plausible explanation for the negative correlation between private tutoring participation and academic achievement. Adding this MTS assumption significantly increases the lower bound. Under MTS assumption the lower bound for the 95% distribution, for example, is measured to be -40 for reading, notably improved compared with the worst-case lower bound of -170.

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[13] Manski and Pepper (2011) applied the method of restricting the minima and maxima.
[14] Confidence intervals are estimated by using the variation around lower and upper bound with 300 pseudosamples.

[Figure 3a near here]

[Figure 3b near here]

Combining the MTS and MIV assumptions does not further reduce the lower bound, but significantly reduces the upper bound, for example in reading to 60 compared with the worst-case upper bound of 150. While adding this MIV assumption substantially reduces the ambiguity created by the selection problem, there still remains uncertainty about the ATE. Calculating the MTS-MIV bounds in reading for the different school tracks the bounds narrow to [2, 60] for the intermediate track: i.e., the impact of private tutoring appears to be at least slightly beneficial in reading. While this bound is positive, the confidence interval includes zero and therefore I cannot reject the hypothesis that private tutoring is ineffective for all students. The narrowest bounds are found for students in the upper-level school track. However, all MTS-MIV bounds exclude the ETS point estimate.

[Figure 4a near here]

[Figure 4b near here]

Imposing all three assumptions (MTR, MTS, MIV) jointly leads to the bounds in Figure 4a and 4b. The combined assumptions increase the lower bound significantly in reading and mathematics. Adding this additional MTR assumption implies that the ATE must be nonnegative, private tutoring can therefore not increase the probability of a low academic outcome.

The calculated bounds demonstrate that additional assumptions can have substantial identifying power compared to the worst-case bounds, as the lower and upper bounds shrink. While these findings indicate that private tutoring improves students' academic achievement in reading in the intermediate level school track, these results have to be interpreted carefully. The 95% confidence interval includes zero and thus, I cannot reject the hypothesis that private tutoring is ineffective.

Even though the imposed assumptions are relatively weak and plausible, there is still a large ambiguity concerning the impact of private tutoring on students' academic achievement in reading and mathematics. I cannot reject the hypothesis that private tutoring is ineffective in promoting good academic outcome.

5 Conclusion

Regressing students' academic achievement on private tutoring lessons generally gives large negative estimates. Since there is a high probability of a negative selection into private tutoring these estimates are not all informative about the causal effect of private tutoring on students' academic outcome. Therefore, different identification strategies have been used in the empirical literature to estimate the true causal effect of private tutoring. The empirical evidence shows mixed effects for point estimates on the effect of private tutoring on achievement.

The present study contributes to the literature by applying an alternative method to overcome the selection bias and to identify the effect. This article uses a nonparametric bounds method to analyse the causal effect of private tutoring by relying on a set of relatively weak nonparametric assumptions. The step-by-step approach applied in this paper allows the reader to identify which assumptions tighten the bounds in which direction. Moreover, the analysis drops the probably rather unrealistic assumption of a linear and homogenous effect of private tutoring lessons on students' academic achievement. The applied method obtains bounds around the average treatment effect even when the treatment effect differs between schools or students.

Four my preferred MTS-MIV models, the results imply that private tutoring leads to academic achievement in reading for students in the intermediate track. In particular, estimates reveal that private tutoring increases achievement by at least 5.8 per cent of a standard deviation. Although these results suggest that private tutoring leads to notable improvements in students' academic achievement in reading, I cannot reject the hypothesis that private tutoring may be ineffective for the students outcome.

However, the identified bounds are still quite large and – apart from private tutoring in reading in the intermediate track and the controversial MTR bounds – include zero. The reason for the latter might be the different kinds of private tutoring, indicating that there is a heterogeneous and probably not linear effect of private tutoring on students' achievement in reading and mathematics. Different kind of tutors (e.g. retired teacher, students, older pupils), different settings (e.g. one-to-one, two-to-one) or different frequencies (once a week or twice a week) might have a different impact on students and, therefore, more research is needed to be able to rate the different forms of private tutoring and to further tighten the bounds for different sub-samples.

Appendix

Table 2: Self-learning time and tutoring in reading and mathematics, PISA 2006

self-learning time per week	no tutoring reading N	%	tutoring in reading N	%	no tutoring in math N	%	tutoring in math N	%
no time	1621	12.55	302	5.76	1082	9.95	380	5.21
less than 2 hours	9195	71.16	3200	61.11	6881	63.28	4147	56.93
2 up to 4 hours	1840	14.24	1322	25.25	2511	23.09	2113	29.01
4 up to 6 hours	223	1.72	309	5.91	327	3.01	466	6.4
6 or more hours	43	0.33	103	1.97	73	0.67	178	2.44
Total	12922		5237		10875		7284	

Table 3: Self-learning time in reading per week, PISA 2006

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                                self-learning         > 4 hours self-learning
                            (1)           (2)          (3)            (4)
--------------------------------------------------------------------------------

tutoring in reading     0.427***      0.539***      0.629***       0.552***
                        (8.72)        (9.60)        (10.55)        (9.11)

female                                0.369***                     0.119**
                                      (8.02)                       (1.96)

age                                   0.0566                       0.143***
                                      (1.57)                       (2.69)

immigrant                             0.218***                    -0.212***
                                      (3.66)                       (-3.03)

parent education                     -0.00566                      0.0217**
                                     (-0.80)                       (2.03)

highest parental ISEI                -0.00258*                    -0.00192
                                     (-1.81)                       (-1.11)

canton                               -0.00290                      0.0177***
                                     (-0.98)                       (4.31)

PISA read                             0.00249***                  -0.00145***
                                      (8.46)                       (-3.68)
--------------------------------------------------------------------------------
Observations            18159         18159         18159          18159
--------------------------------------------------------------------------------
Marginal effects; t statistics in parentheses
 (d) for discrete change of dummy variable from 0 to 1
* p<0.10, ** p<0.05, *** p<0.01
```

Table 4: Self-learning time in mathematics per week, PISA 2006

```
--------------------------------------------------------------------------------
                                Self-learning         > 4 hours self-learning
                            (1)           (2)          (3)            (4)
--------------------------------------------------------------------------------

tutoring in math        0.340***      0.394***      0.439***       0.378***
                        (7.89)        (8.14)        (9.72)         (8.31)

female                                0.457***                    -0.00356
                                      (11.09)                      (-0.07)

age                                   0.0461                       0.0181
                                      (1.22)                       (0.43)
```

15

```
immigrant                              0.174***                    -0.113
                                       (2.97)                     (-1.61)

parent education                      -0.0113                      0.0147*
                                      (-1.30)                      (1.65)

highest parental I~I               0.0000134                   -0.000218
                                       (0.01)                     (-0.13)

canton                              -0.00666**                   0.00887***
                                      (-2.10)                      (2.58)

PISA math                           0.00115***                 -0.00157***
                                       (3.48)                     (-4.25)
------------------------------------------------------------------------
Observations         18159             18159         18159          18159
------------------------------------------------------------------------
Marginal effects; t statistics in parentheses
 (d) for discrete change of dummy variable from 0 to 1
* p<0.10, ** p<0.05, *** p<0.01
```

References

Baker, D. P., & LeTendre, G. K. (2005). *National differences, global similarities: World culture and the future of schooling*. California: Stanford University Press.

Banerjee, A. V., Cole, S., Duflo, E., & Linden, L. (2007). Remedying Education: Evidence from Two Randomized Experiments in India. *The Quarterly Journal of Economics*, *122*(3), 1235 –1264. doi:10.1162/qjec.122.3.1235

Beresteaunu, A., & Manski, C. F. (2000). Bounds for STATA: Draft Version 1.0.

Björklund, A., & Salvanes, K. G. (2011). *Education and Family Background: Mechanisms and Policies* (Handbook of the Economics of Education) (S. 201– 247). Elsevier. Abgerufen von http://ideas.repec.org/h/eee/educhp/3-03.html

Black, S. E., & Devereux, P. J. (2011). *Recent Developments in Intergenerational Mobility* (Handbook of Labor Economics) (S. 1487–1541). Elsevier. Abgerufen von http://ideas.repec.org/h/eee/labchp/5-16.html

Blundell, R., Gosling, A., Ichimura, H., & Meghir, C. (2007). Changes in the Distribution of Male and Female Wages Accounting for Employment Composition Using Bounds, *75*(2), 323–363.

Boes, S. (2010). Nonparametric Analysis of Treatment Effects in Ordered Response Models. Abgerufen von http://ideas.repec.org/p/soz/wpaper/0709.html

Bray, M. (1999). The shadow education system: private tutoring and its implications or planners. Fundamentals of educational planning No. 61. *International Review of Education*, *46*(6), 641–644. doi:10.1023/A:1026531112211

Bray, M. (2011). *The Challenge of Shadow Education*. NESSE.

Dang, H.-A., & Rogers, F. H. (2008). The Growing Phenomenon of Private Tutoring: Does It Deepen Human Capital, Widen Inequalities, or Waste Resources? *The World Bank Research Observer*, *23*(2), 161 –200. doi:10.1093/wbro/lkn004

Gerfin, M., & Schellhorn, M. (2006). Nonparametric bounds on the effect of deductibles in health care insurance on doctor visits - Swiss evidence. *Health Economics*, *15*(9), 1011–1020.

Gundersen, C., Kreider, B., & Pepper, J. (2012). The impact of the National School Lunch Program on child health: A nonparametric bounds analysis. *Journal of Econometrics*, *166*(1), 79–91. doi:10.1016/j.jeconom.2011.06.007

Haan, M. de. (2011). The Effect of Parents' Schooling on Child's Schooling: A Nonparametric Bounds Analysis. *Journal of Labor Economics*, *29*(4), 859–892. doi:10.1086/660798

Heckman, J. J., & Leamer, E. E. (2007). *Handbook of econometrics*. Elsevier.

Heckman, J. J., & Vytlacil, E. J. (2000). *Instrumental Variables, Selection Models, and Tight Bounds on the Average Treatment Effect*. National Bureau of Economic Research, Inc. Abgerufen von http://ideas.repec.org/p/nbr/nberte/0259.html

Jacob, B. A., & Lefgren, L. (2004). Remedial education and student achievement: A regression-discontinuity analysis. *Review of Economics and Statistics*, *86*(1), 226–244.

Jung, J. H., & Lee, K. H. (2010). The determinants of private tutoring participation and attendant expenditures in Korea. *Asia Pacific Education Review*, *11*(2), 159–168. doi:10.1007/s12564-009-9055-7

Kang, C. (2011). Family Size and Educational Investments in Children: Evidence from Private Tutoring Expenditures in South Korea. *Oxford Bulletin of Economics and Statistics*, *73*(1), 59–78.

Kreider, B., Pepper, J. V., Gundersen, C., & Jolliffe, D. (2012). Identifying the Effects of SNAP (Food Stamps) on Child Health Outcomes When Participation Is Endogenous and Misreported. *Journal of the American Statistical Association*, *107*(499), 958–975.

Lavy, V., & Schlosser, A. (2005). Targeted Remedial Education for Underperforming
Teenagers: Costs and Benefits. *Journal of Labor Economics*, *23*(4), 839–874.

Lee, J. Y. (2013). Private tutoring and its impact on students' academic achievement,
formal schooling, and educational inequality in Korea (Doctoral dissertation).
Abgerufen von http://academiccommons.columbia.edu/catalog/ac:161564

Manski, C. F. (1990). Nonparametric Bounds on Treatment Effects. *American Economic
Review*, *80*(2), 319–23.

Manski, C. F. (1997). Monotone Treatment Response. *Econometrica*, *65*(6), 1311–1334.

Manski, C. F. (2007). *Identification for Prediction and Decision*. Harvard University
Press.

Manski, C. F., & Pepper, J. V. (2000). Monotone Instrumental Variables, with an
Application to the Returns to Schooling. *Econometrica*, *68*(4), 997–1012.

Manski, C. F., & Pepper, J. V. (2009). More on monotone instrumental variables.
Econometrics Journal, *12*(1), 200–216.

Manski, C. F., & Pepper, J. V. (2011). Deterrence and the death penalty: Partial
identification analysis using repeated cross sections. Presented at the PhD Course
University of Berne. Abgerufen von
http://www.vwl.unibe.ch/research/seminar/pdf/prof_charles_manski_2011-09-
01.pdf

Mariotta, M. (2006). Il ricorso a lezioni private nella scuola media. *Scuola ticinese*, (275 /
2006), 14 – 16.

Mariotta, M., & Nicoli, M. (2005). Il ricorso a lezioni private nella scuola media.
Repubblica e Cantone del Ticino.

OECD. (2009). *PISA Data Analysis Manual: SPSS* (Second Edition.). OECD Publishing.

OECD. (2011a). *PISA 2009 Technical Report (Preliminary version)*. OECD Publishing.
Abgerufen von

http://www.oecd.org/document/19/0,3746,en_2649_35845621_48577747_1_1_1_1,00.html

OECD. (2011b). *Quality time for students: Learning in and out of school*. OECD Publishing.

Ono, H. (2007). Does examination hell pay off ? A cost-benefit analysis of „ronin" and college education in Japan. *Economics of Education Review*, *26*(3), 271–284.

Pinkovskiy, M. L. (2013). World welfare is rising: Estimation using nonparametric bounds on welfare measures. *Journal of Public Economics*, *97*(C), 176–195.

Ritter, G. W., Barnett, J. H., Denny, G. S., & Albin, G. R. (2009). The Effectiveness of Volunteer Tutoring Programs for Elementary and Middle School Students: A Meta-Analysis. *Review of Educational Research*, *79*(1), 3 –38. doi:10.3102/0034654308325690

Southgate, D. E. (2009). *Determinants of Shadow Education: A Cross-National Analysis* (thesis). Abgerufen von http://etd.ohiolink.edu/view.cgi/Southgate%20Darby%20E.pdf?osu1259703574

Suryadarma, D., Suryahadi, A., Sumarto, S., & Rogers, F. H. (2006). Improving Student Performance in Public Primary Schools in Developing Countries: Evidence from Indonesia. *Education Economics*, *14*(4), 401–429.

Tables

Table 1: Descriptive statistics of the sample

| Variable	no private tutoring			private tutoring in reading			private tutoring in mathematics		
	N	Mean	SD	N	Mean	SD	N	Mean	SD
female	13472	0.51	0.5	1216	0.49	0.5	2757	0.6	0.49
age	13472	15.76	0.63	1216	15.88	0.66	2757	15.76	0.63
tertiary education	13472	0.55	0.5	1216	0.59	0.49	2757	0.6	0.49
secondary education	13472	0.1	0.3	1216	0.11	0.31	2757	0.1	0.31
vocational education	13472	0.31	0.46	1216	0.25	0.43	2757	0.27	0.44
no postobligatory	13472	0.03	0.18	1216	0.05	0.22	2757	0.03	0.18
first gen	13472	0.09	0.29	1216	0.16	0.37	2757	0.1	0.3
second gen	13472	0.3	0.46	1216	0.35	0.48	2757	0.35	0.48
native	13472	0.61	0.49	1216	0.49	0.5	2757	0.55	0.5
foreign lang	13472	0.15	0.36	1216	0.25	0.43	2757	0.17	0.37
ISEI	13472	51.02	15.83	1216	50.52	15.92	2757	52.19	15.3
siblings	13472	0.89	0.32	1216	0.87	0.34	2757	0.85	0.36
single	13472	0.14	0.35	1216	0.14	0.35	2757	0.14	0.35
mixed	13472	0	0.06	1216	0.01	0.09	2757	0	0.07
nuclear	13472	0.86	0.35	1216	0.85	0.36	2757	0.85	0.35
latin Swiss	13472	0.28	0.45	1216	0.29	0.46	2757	0.33	0.47
upper level track	13472	0.35	0.48	1216	0.24	0.43	2757	0.35	0.48
intermediate track	13472	0.39	0.49	1216	0.39	0.49	2757	0.4	0.49
basic level track	13472	0.25	0.44	1216	0.34	0.47	2757	0.23	0.42
PISA read	13472	510.8	85.01	1216	473.92	89.8			
PISA math	13472	545.25	92.4				2757	519.45	88.36

Figures

Figure 1: How MTS and MTR tighten the bounds in the binary case

E[y(1)]: private tutoring
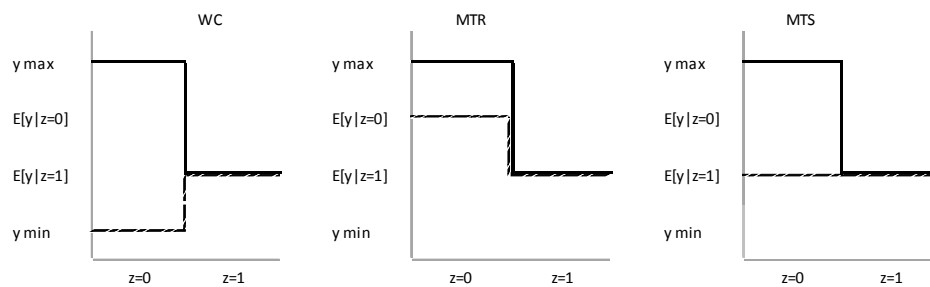
E[y(0)]: no private tutoring
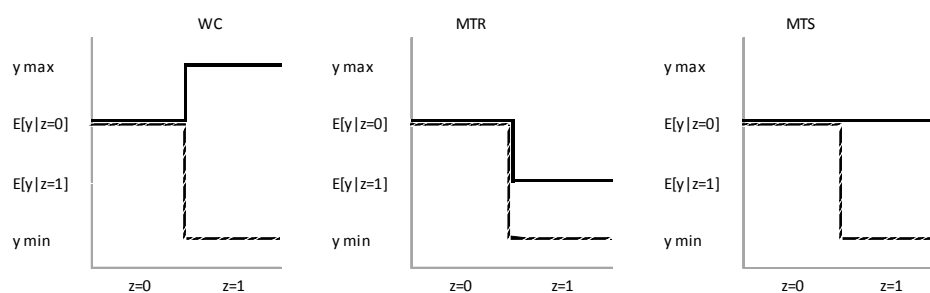
Source: Figure based on Haan (2011).

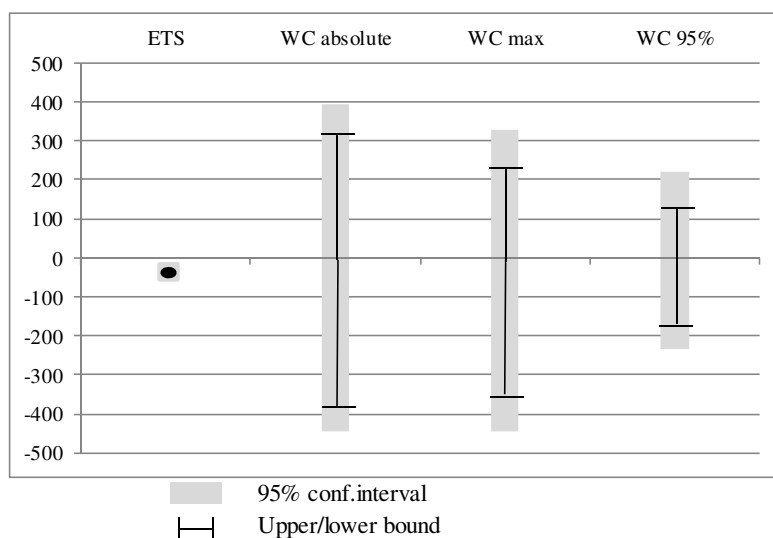Figure 2a: Exogenous treatment selection and worst-case bounds on the ATE in reading

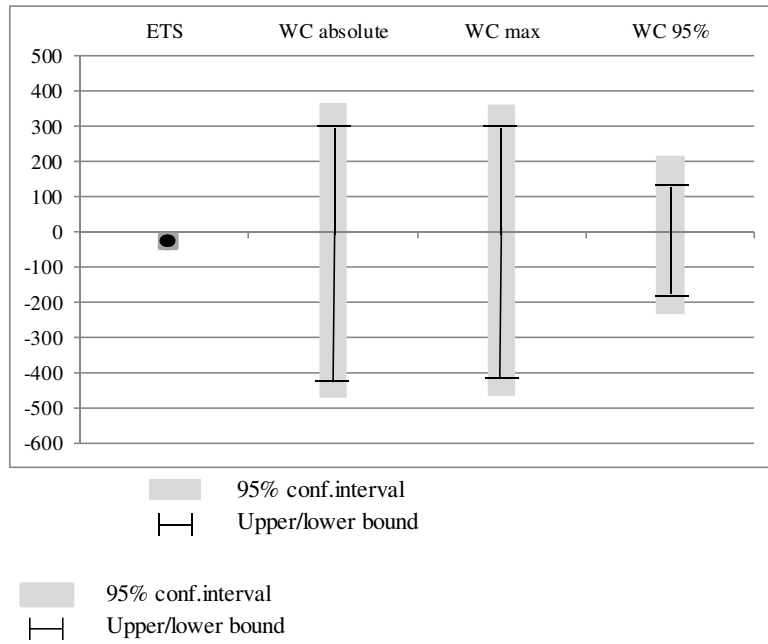Figure 2b: Exogenous treatment selection and worst-case bounds on the ATE in mathematics

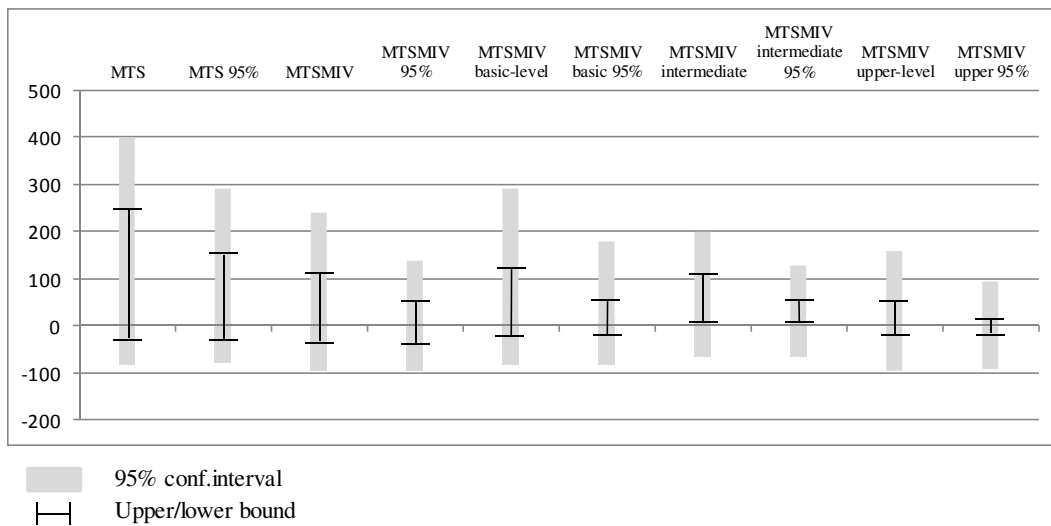Figure 3a: Bounds on the ATE in reading: MTS, joint MTS and MIV assumptions

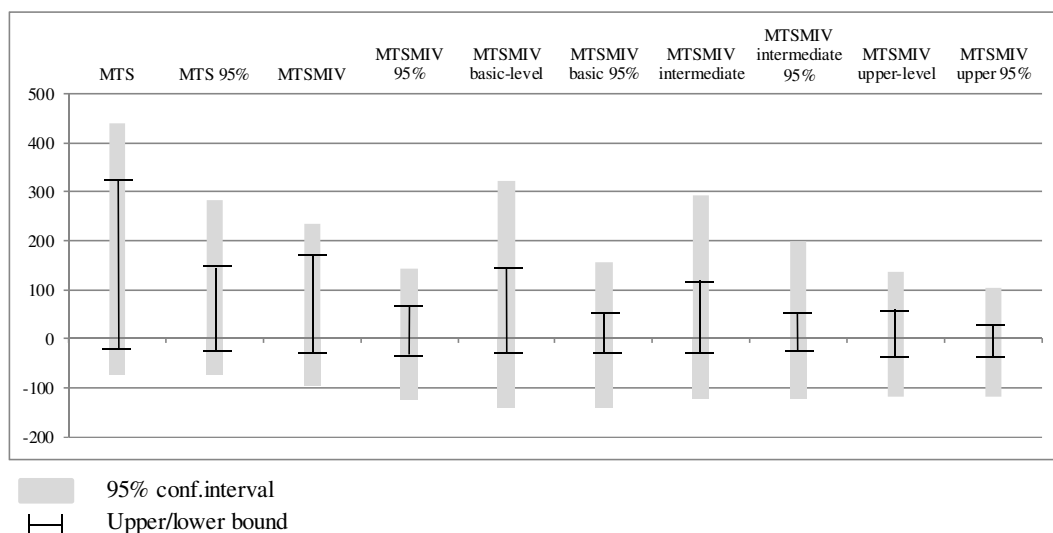Figure 3b: Bounds on the ATE in mathematics: MTS, joint MTS and MIV assumptions

Figure 4a: Bounds on the ATE in reading: Joint MTS, MTR and MIV assumptions
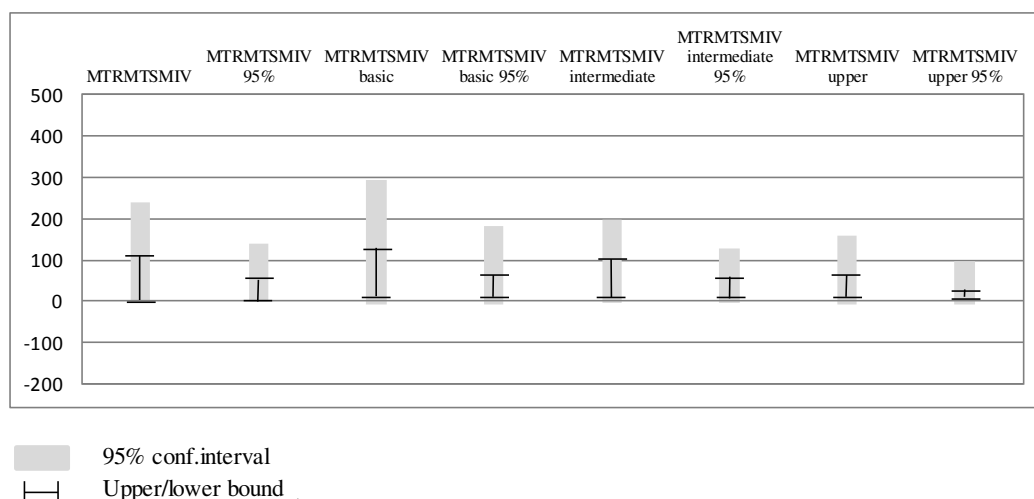

Figure 4b: Bounds on the ATE in mathematics: Joint MTS, MTR and MIV assumptions