Does Private Tutoring Work?

The Effectiveness of Private Tutoring: A Nonparametric Bounds Analysis

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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 and 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. The tightest bounds show that private tutoring has significantly positive effects on student’s mathematics and reading test scores.

Keywords: C14, C21, I21

JEL classification: Partial identification, selection problem, nonparametric bounds method, monotone instrument variable, private tutoring, academic achievement
1 Introduction

Private tutoring – fee-based tutoring outside of the normal school in academic subjects - has become popular all over the world (Baker and LeTendre 2005; Bray 1999, 2011; Dang and Rogers 2008; Jung and Lee 2010; Mariotta and 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 a student’s academic performance. Recent literature shows mixed evidence, but mostly positive effects of tutoring on students’ academic outcomes.


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 fundamental problem 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. Using a quasi-experimental technique to analyze the treatment effect requires strong distributional assumptions and tight parametric restrictions, such as distributional assumptions, that may be violated by the data at hand. 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. 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. This bounds method has been applied, for example, in different recent studies (Blundell et al. 2007; Boes 2010; Gerfin and Schellhorn 2006; Gundersen, Kreider, and J. Pepper 2012; Haan 2011; Kang 2011; Manski and J. V. Pepper 2011). There exists no study, though, that applies this method to identify the causal impact of private tutoring on student achievement.

Given the conflicting findings concerning the effectiveness of private tutoring in the literature and the methodological challenges addressing the selection problem, bounds under weaker assumptions seem to be more plausible. The price to be paid for greater credibility is that the parameter of interest will be only partially identified. However, these bounds on the average treatment effect of private tutoring are an important step towards identifying the causal effect of private tutoring on a students’ academic achievement. Using a representative dataset of the Swiss
PISA 2009 cohort this paper analyzes the question whether participation in private tutoring lessons has a causal effect on student academic achievement in mathematics and reading.\textsuperscript{1}

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 response (MTR) that means the effect of private tutoring to be positive. Second this study applies monotone treatment selection (MTS) assumption that states that attending private tutoring classes is weakly monotonically related with poor academic outcomes. Third it will use the parents’ education as a monotone instrument variable (MIV).

The tightest bounds show a positive causal impact of private tutoring lessons on a student’s academic achievement, both in mathematics and reading test scores. Although the method does not allow calculating point estimates but produces a range of potential effects.

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.

\section{Swiss education system and data}

\subsection{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\textsuperscript{2}. 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). Some cantons offer integrative tracks, in which pupils are sorted to one track or the other depending on the subject, as well as cooperative tracks, in which all school tracks are in the same building in order to offer greater accessibility and permeability.

After finishing the compulsory school (9th grade) students choose among two different possibilities: Going to a full-time educational school (Gymnasium or Fachmittelschule) or choosing a vocational track (apprenticeship training). In Switzerland, about 20 percent of school leavers attend a Baccalaureate school (Gymnasium), which prepares for university. The criteria for admission to Baccalaureate schools differ considerably from canton to canton. Generally

\textsuperscript{1} In a next step the author plans to calculate nonparametric bounds for the ordered PISA outcome (competence level) based on (Boes 2013).

\textsuperscript{2}The equivalent of states in the US
students form upper-level school track are considered for admission. In around half of the Swiss cantons the student’s school or teacher’s recommendation determines whether he or she will be able to enroll in a Baccalaureate school. In the other half of the cantons an entrance exam is required (SKBF 2011). About 60 percent 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 of formal schooling in a vocational school. The two main types of apprenticeship training programs last either three or four years. Due to a widely spread distrust in the value of school grades, Swiss employers utilize external, standardized aptitude test results (e.g. “multicheck”) instead of school grades when recruiting new apprentices.

2.2 Private tutoring in Switzerland

Private tutoring in Switzerland takes mainly two different forms. The first type is one-to-one instruction by a privately-paid teacher either at the teacher’s house or at the student’s house. 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 centers usually own or rent multi-story buildings in the city centers. Students attend these centers outside formal school hours. These centers 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. Analyzing TIMSS data from 1995 Baker and 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 focuses on reading (OECD 2011).

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 weight 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 8/9\textsuperscript{th} grade among the 9\textsuperscript{th} graders. The analysis in this paper makes use of the national 9\textsuperscript{th} grade survey with 13\textsuperscript{,}472\textsuperscript{3} students.

The nationwide representative PISA 2009 dataset shows a participation rate in private tutoring of 30\% for Switzerland (Hof and Wolter 2012) for 9\textsuperscript{th} 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. Participation in private tutoring lessons in reading depends, not surprisingly, heavily on the migration status and the language spoken at home. For lessons in mathematics, having siblings has a negative effect on the probability of participation. This indicates that siblings can serve as a substitution for private tutoring in mathematics or reading.\textsuperscript{4} Moreover, the evidence identifies strong regional differences in the demand of private tutoring.

The main outcome variable is the student’s academic achievement. Academic achievement is measured with the PISA 2009 scores of Swiss 9\textsuperscript{th} 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 more detail in the next section. Table 1 shows the descriptive statistics for students without any private tutoring and with private tutoring in language (reading) and mathematics.

\textsuperscript{3} Due to item non-response 2383 observations were deleted.
\textsuperscript{4} Controlled for an approximation of the households income (International Socio-Economic Index of Occupational Status (ISEI)).
I consider the problem of learning the effect of private tutoring on student academic achievement (in mathematics and reading). The analysis wants to identify the average treatment effect (ATE) of going to private tutoring classes on a student’s achievement, that is,  \[ ATE_{r,m}(1,0) = E[y(1)|x] - E[y(0)|x] \]  

Where \( y \) is the student’s academic achievement in PISA and \( y(1) \) 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 (Beresteanu and 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.

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5 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.
For each student we do not observe one of the two potential outcomes \( z = 0 \) (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 and J. V. Pepper 2009; Manski 1990, 2007) and imposes as little assumptions as possible to calculate a lower and an upper bound of the 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.\(^6\)

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. \( z \in T \) denotes as well the treatment received by person. \( z = 1 \) denotes that a student participated in private tutoring in the 8th or 9th grade in mathematics or reading and \( z = 0 \) otherwise. The response function \( y(.) : T \rightarrow Y \) maps the treatments \( t \in T \) into outcomes \( y(t) \in Y \). \( y(t)(t=z) \) 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 and J. V. 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.

### 5.1 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:

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

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

\(^6\) It is important to notice, that these bounds are not confidence intervals. They express the ambiguity created by the selection problem (Manski and J. V. Pepper 2011).
And the resulting bound on the ATE\(^7\) is
\[
E[y(1)|z=1] P(z=1) + K_0 * P(z=0) - [E[y(0)|z=0] P(z=0) + K_1 * P(z=1)] 
\leq E[y(1)] - E[y(0)] \leq 
E[y(1)|z=1] P(z=1) + K_1 * P(z=0) - [E[y(0)|z=0] P(z=0) + K_0 * P(z=1)]
\]

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\(^8\) 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 response assumption, the monotone treatment selection assumption and a monotone instrument variable.

Figure 1: Nonparametric bounds in the binary case

![Figure 1: Nonparametric bounds in the binary case](image)

5.2 Monotone treatment response (MTR)

The first assumption employed is the monotone treatment response (MTR) (Manski 1997). MTR states that the outcome is 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 a student’s academic performance. This assumption is strong but fostered by the recent literature

\(^7\) 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.

\(^8\)Mansi bounds are sharp bounds, i.e. nothing else can be learned in face of the censored data. Proof in (Heckman and Leamer 2007; Heckman and Vytlacil 2000; Manski 2007).
presented and therefore plausible.\textsuperscript{9} It is hard to imagine, that parents sent their children to private tutoring classes when there is a negative impact on the student’s academic achievement. MTR allows estimating whether there exists a positive effect of private tutoring or whether there is no effect at all. Moreover the estimations provide bounds for the effect size. 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 student’s performance:

\[
E[y(1)|z=0] \geq E[y(0)|z=0] \\
E[y(1)|z=1] \geq E[y(0)|z=1]
\]  \[5\]

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 on \( E[y(1)] \) under MTR can be expressed by:

\[
E[y|z=0] \leq E[y(1)] \leq E[y|z=1] P(z=1) + K_1*P(z=0) \\
E[y|z=0] P(z=0) + K_0*P(z=1) \leq E[y|z=0] \leq E[y|z=1]
\]  \[6\]  \[7\]

5.3 Monotone treatment selection (MTS)

A second 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

\textsuperscript{9} One possible reason of a negative effect of private tutoring on a student’s academic outcome is imaginable: It might happen that other resources used for student support (e.g. parents’ help with homework) are crowded out and therefore attending private tutoring might have a negative effect on a students’ achievement.
participated in private tutoring.\textsuperscript{10} 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 student 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 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:

\[
E[y|z=1] \leq E[y(1)] \leq E[y(1)|z=1] \cdot P(z=1) + K_1 \cdot P(z=0) \tag{8}
\]

\[
E[y(0)|z=0] \cdot P(z=0) + K_0 \cdot P(z=1) \leq E[y(0)] \leq E[y|z=0] \tag{9}
\]

If I impose MTR as well as MTS the lower bound for \(E[y(1)]\) is the higher lower bound of MTR and MTS, which is \(E[y|z=0]\). The upper bound on \(E[y(0)]\) is the lower bound of MTR and MTS, which is \(E[y|z=1]\).

\section*{5.4 Monotone instrument variable (MIV)}

A third 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 and J. V. Pepper 2000).

This approach applies the traditional IV\textsuperscript{11} but loosens the assumptions with mean monotonicity (MIV)\textsuperscript{12} (Manski and J. V. Pepper 2000):

\[
u_1 \leq u \leq u_2 \rightarrow E[y(t)|v=u_1] \leq E[y(t)|v=u] \leq E[y(t)|v=u_2] \tag{10}
\]

In contrast to an instrumental variable assumption with mean independence, the monotone instrumental variable assumption allows a weakly monotone positive relationship between \(v\) and

\textsuperscript{10} 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 our assumption do not warrant unquestioned acceptance, they certainly are plausible.

\textsuperscript{11} For example Ono (2007) uses tutoring during secondary education as in IV to measure the effect of tutoring in tertiary education.

\textsuperscript{12} The identifying power of an MIV is examined in (Manski and J. V. Pepper 2000).
the mean potential outcome (Manski and J. V. 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. The MIV assumption allows for a direct impact of the parents education on a student’s 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 and Salvanes 2011; Black and Devereux 2011).

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

$$
\sum_{u \in V} P(v=u) \left\{ \sup_{u_1 \leq u} \{ E(y|v= u_1, z=1) P(z=1|v= u_1) + K_0 \cdot P(z=0|v= u_1) \} \right\}
\leq E[y(1)] \leq
\sum_{u \in V} P(v=u) \left\{ \inf_{u_2 \geq u} \{ E(y|v= u_2, z=1) P(z=1|v= u_2) + K_1 \cdot P(z=0|v= u_2) \} \right\}
$$

From Equation [10] and [11] 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.

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.

This paragraph is structured as follows: First worst case nonparametric bounds are shown; next MTS, MTR and MIV assumptions are applied. The analyses are also shown for a subsample with the maximum and minimum PISA points of the 95% of all students.

Figure 3 shows the worst-case nonparametric bounds on a student’s academic achievement in reading (Figure 3a) and mathematics (Figure 3b) as a function of attending private tutoring lessons or not. Logically the PISA results of student can never be lower than 0 points and never higher than 1000 points. Realized PISA points 2009 for reading and mathematics lie between the interval 120 and 860. Thus, it seems reasonable to assume $E[y(1)|z=0] \in [120, 860]$. Therefore

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

14 Proof see (Manski and J. V. Pepper 2000).

15 Manski and Pepper (2011) applied the method of restricting the minima and maxima on death penalties.
\( E[y(1)] \in \{E[y(1)|z=1] P(z=1) + 120P(z=0), E[y(1)|z=1] P(z=1) + 860P(z=0)\} \) and \( E[y(0)] \) analogous. Evaluating these worst-case bounds with \( E[y(1)|z=1] = 474, P(z=1) = 0.098 \) and \( E[y(0)|z=0] = 515 \) shows for test language \( E[y(1)] \in [155.4, 821.4] \) and \( E[y(0)] \in [475.5, 549.5] \). 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 \([-422, 318]\).

These are very weak bound assumptions on the counterfactual student’s achievement. Using the actual maximum and minimum points in PISA 2009 for reading (124, 771) and mathematics (125, 856) the bounds shrink a little bit and the ATE for test language 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 percent minimum and maximum to calculate the upper and lower worst-case bounds, the ATE for reading is in the interval \([-171, 225]\) and for mathematics must be in the interval \([-184, 241]\).

Applying the very weak assumption that the students will score somewhere in between where 95 percent of all students do allows us to reduce the interval for the ATE significantly.

Figure 3a: Worst-case bounds language  
Figure 3b: Worst-case bounds mathematics

Even though the worst case bounds are still rather wide, the lower bound increases substantially by adding weak nonparametric assumptions (Figure 4a and 4b). Adding the MTR assumption strongly reduces the width of the bounds, in particular when the calculation uses the minimum and maximum PISA points which 95 percent of all students reach.

Using the parents’ educational schooling as an MIV leads to even narrower bounds. Imposing all three assumptions (MTR, MTS, MIV) jointly leads to the last bounds in Figure 4a and 4b, which show that attending private tutoring classes increases test scores in reading by at least 52 percent of a standard deviation and in mathematics by at least 47 percent. The bounds in Figure 4a and 4b demonstrate that additional assumptions can have substantial identifying power compared to the worst-case bounds (Figure 3a, 3b), as the lower and upper bounds shrink.

Figure 4a: Bounds language
The results suggest that ETS point estimates are a result of a negative selection into private tutoring. The bounds on the other hand show a positive impact of private tutoring on performance.
5 Conclusion

Regressing student’s 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 a student’s 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 analyze the causal effect of private tutoring by relying on a set of 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 a student’s academic achievement. The applied method obtains bounds around the average treatment effect even when the treatment effect differs between schools or students.

Introducing relatively weak nonparametric assumptions lead to bounds that show that attending private tutoring classes significantly increases a students’ outcome in mathematics and reading. Students attending private tutoring lessons perform significantly and substantially better on the student achievement tests than students without private tutoring. The tightest bounds show that having private tutoring lessons increases a student’s academic outcome by at least 52 percent of a standard deviation in mathematics and 47 percent of a standard deviation in reading.

Despite the positive effects, the identified bounds are still quite large. The reason for the latter might be the different kinds of private tutoring. There are different 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) 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.
6 References


