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The Effect of Additional Funds for Low-Ability Pupils – A Nonparametric Bounds Analysis

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The Effect of Additional Funds for Low-Ability Pupils – A Nonparametric Bounds Analysis

Abstract

This paper investigates the effect of a policy measure that gives secondary schools additional resources for low-ability pupils. Schools are free in deciding how to spend the additional money. I use a nonparametric bounds analysis to estimate upper and lower bounds on the effect of additional funds on exam results of pupils. First I investigate what can be concluded without imposing assumptions; next I layer weak nonparametric assumptions to tighten the bounds. The tightest bounds show that the additional school funds significantly increase the probability that a pupil passes the exam and it significantly increases math and language test scores.

JEL-Code: I200, C140, C310.

Keywords: school resources, nonparametric bounds, education, spillovers.

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1 Introduction

One of the most important and controversial topics in the economics of education is the effect of school resources on pupil outcomes. It is an important topic because changing school resources is one of the key policy measures available to governments. It is controversial because there is no consensus in the literature about whether or not increasing school resources improves pupil achievement. Hanushek (2006) gives an overview of the literature and concludes that there is little consistent relationship between resources to schools and student achievement.¹ This absence of a consistent relationship could potentially be explained by the fact that many studies ignore endogeneity problems. Obtaining a credible point estimate of the causal effect of school resources is typically not easy. Policy measures regarding the amount of money given to schools are generally implemented nationwide, and when there is variation in school resources between schools, it is often correlated with (un)observed school and pupil characteristics.

There are a number of recent studies that use a quasi-experimental design, such as difference-in-differences, regression discontinuities, or an instrumental variable approach, to identify the causal impact of school resources. Also these recent studies obtain contradictory findings. Papke (2005), Machin et al. (2010), Holmlund et al. (2010) and Gibbons et al. (2012) all find positive effects of an increase in school resources on pupils achievement, while Bénabou et al. (2009) find no significant effect of additional school resources. Leuven et al. (2007) and Van der Klaauw (2008) even find negative point estimates, which are in some cases significantly different from zero. These diverging findings might be due to the fact that the investigated policy measures differ in the amount of additional resources and the degree of freedom the schools have in spending these resources. In addition these papers rely on different assumptions to obtain point identification and, when treatment response is heterogeneous, they obtain estimates of local average treatment effects. Violations of the identifying assumptions or estimation of different local average treatment effects can therefore also explain the contradictory findings.

¹See also Krueger (2003) and Hanushek (2003) for a discussion about the effect of school resources.

This paper studies the impact of school resources on pupil achievement by investigating the effect of a policy measure in the Netherlands (Learning Support) that gives additional funds to secondary schools for each low-ability pupil that is enrolled in the school. Schools are free in deciding how to spend the additional money on learning support for low-ability pupils. Like most resource policies, Learning Support is implemented nationwide and there is no exogenous variation that can be exploited to obtain a credible point estimate. I deal with this identification problem by using a nonparametric bounds analysis. This partial identification approach is based on relatively weak assumptions and gives bounds on the average treatment effect, also in the presence of heterogeneity in the impact of Learning Support. Even though this approach produces a range instead of a point estimate, the estimated bounds are informative and show that the additional funds have a significant positive impact on pupil achievement. This conclusion does not change when I take potential spillovers into account. To my knowledge this is the first paper that incorporates potential spillovers in an empirical application of the nonparametric bounds method.

The analysis starts with investigating what can be concluded about the effect without imposing assumptions; next I successively layer nonparametric assumptions to tighten the bounds. I use register data with exam results for all pupils in the final year of secondary education in the Netherlands. Since only pupils with learning and/or behavioral difficulties are eligible for the additional funds, I will use the monotone treatment selection assumption that states that receiving Learning Support is weakly monotonically related to poor potential educational outcomes. In addition I will use the average income in the neighborhood of residence of the pupil as a monotone instrumental variable, thereby assuming that pupils living in a poor neighborhood will on average not have better potential educational outcomes than pupils living in a rich neighborhood.

Since the policy measure is targeted at low-ability pupils, this paper will not only be informative about the impact of school resources but it will also address the question of how to

increase schooling outcomes of low-achieving pupils. There is a lot of emphasis on increasing educational attainment at the lower end of the distribution.² There are however very few studies that investigate the causal effect of programs aimed at increasing schooling outcomes of pupils with learning difficulties.³ The main reason for this gap in the literature is a lack of exogenous variation due to the nonrandom selection of pupils into remedial education programs.

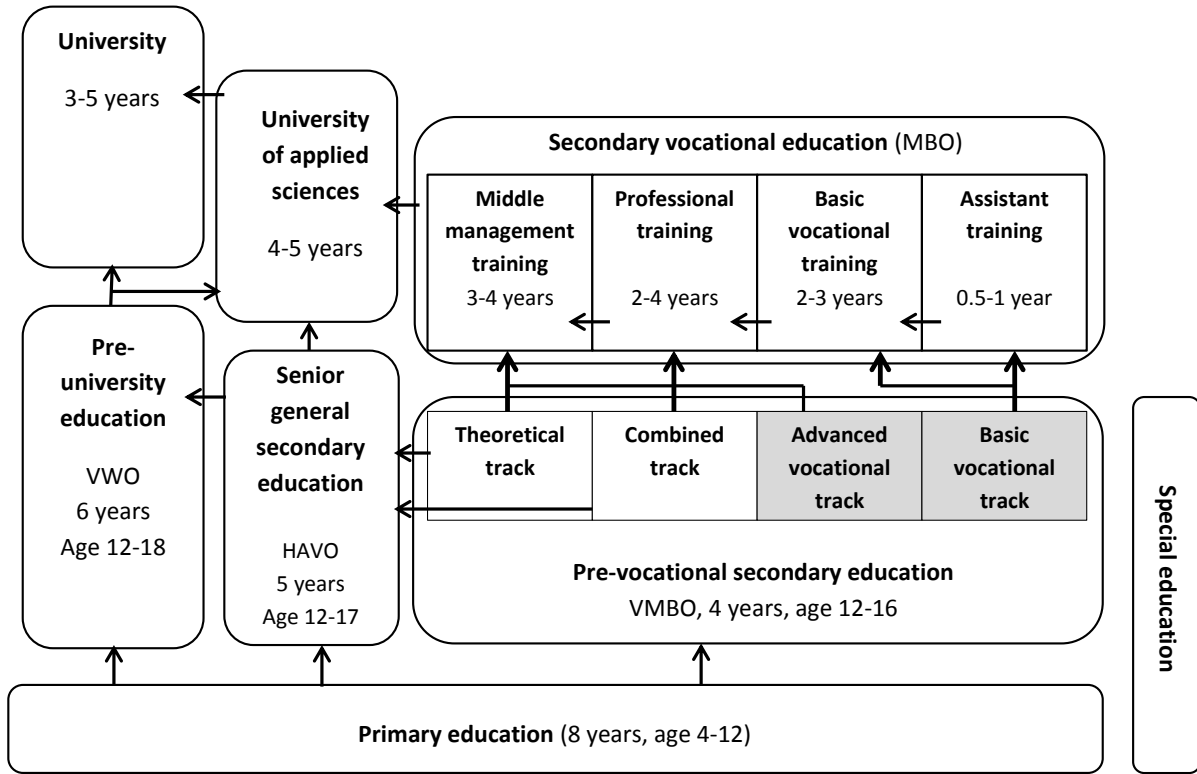
Since Learning Support is a policy measure that affects pupils when they are between 12 and 16 years old, this paper also contributes to the literature on the effectiveness of late versus early childhood interventions. While there is a growing literature that stresses the importance of early childhood interventions (Carneiro & Heckman, 2003), there is not much evidence about the effectiveness of high school interventions. The results of this paper provide evidence that a high school intervention can significantly improve pupil achievement. The estimated lower bounds show that the additional funds for learning support significantly increase the probability that a pupil passes the exam at the end of secondary education and significantly increases both math and language test scores.

The remainder of the paper is structured as follows. Section 2 describes the Dutch educational system, the details of the policy measure and the data. Section 3 explains the identification problem and the nonparametric bounds method. The results will be shown in Section 4 and Section 5 shows results that take into account potential spillovers. Finally Section 6 will summarize and conclude.

²The Europe 2020 strategy, for example, includes the headline target to reduce early school leaving to less than 10 percent by 2020. The motivation for this headline target is that the reduction of early school leaving will not only address the aim of increasing education and training levels in general but it will also address one of the major risk factors for unemployment, poverty and social exclusion (European Council (2011)).

³Exceptions include Hanushek et al. (2002) and Lavy & Schlosser (2005), both studies find a positive impact on pupil achievement.

Figure 1: Dutch educational system



2 Background and data

Dutch educational system

Figure 1 shows an overview of the Dutch educational system. Children are allowed to start school at the day they turn 4 and all pupils up to age 18 are required to go to school until they have obtained a basic qualification.⁴ Children go to secondary education when they are about 12 years old. At the end of primary education most children make a nationwide exit exam that together with the advise of the primary school teacher determines in which track in secondary

⁴A basic qualification is the minimum educational level deemed necessary to find a decent job, or to enroll in higher education. This minimum level of education is set at HAVO or VWO or MBO (level of basic vocational training).

education the pupil can enroll. School choice is free which implies that a pupil can enroll in any school that offers the track that was advised by the primary school.

There are three main tracks in secondary education; pre-vocational secondary education, senior general secondary education and pre-university education. Pre-vocational secondary education is the largest track with about 55 percent of the pupils. As is shown in Figure 1, pre-vocational education consists of four sub-tracks. The basic track has a practical orientation and prepares for basic secondary vocational training. The advanced track also has a practical orientation but prepares for middle and higher levels of secondary vocational education. The theoretical and combined track offer courses of a more advanced level and prepare pupils for middle/ higher levels of secondary vocational education or senior general secondary education.

All secondary schools receive funding from the national government through a “money follows pupil” mechanism. Schools are not allowed to charge compulsory school fees, but they can ask parents for a voluntary contribution which is spent on extracurricular activities. The funding of a school thus depends on the number of enrolled pupils and the yearly amount that the government spends per pupil in secondary education is about 7100 euro’s (Dutch Ministry of Education, 2009).

Learning Support

In 1999 the Dutch government implemented a policy measure, Learning Support, that provides secondary schools that offer pre-vocational secondary education with additional funding for each enrolled pupil with learning or behavioral difficulties.⁵ The government spends about 11100

⁵This policy measure (in Dutch *leerwegondersteunend onderwijs*) was implemented nationwide jointly with the set-up of pre-vocational secondary education which was the result of a merger of three educational tracks (*mavo*, *lbo*, *lo*). It is therefore not possible to use a difference-in-differences, or before-after approach to estimate the effect of the policy on pupil achievement. This is not an issue for the nonparametric bounds analysis applied in this paper.

euro's per year on each pupil that is eligible for Learning Support, which is 4000 euro's more than what the government spends on a regular pupil in secondary education (Dutch Ministry of Education, 2009). Schools can freely decide how to spend this additional money on learning support for eligible pupils. It can range from tutoring and homework assistance, to providing exercises to improve a pupil's studying skills. A pupil can receive learning support in class, but also outside of the classroom. Many schools choose to form small, separate classes with pupils that receive Learning Support such that they can give more individual attention to each of these pupils (Dutch Ministry of Education, 2012).

At the moment of enrollment a secondary school can start an investigation into whether a pupil needs learning support. This assessment is usually initiated on the basis of advice of the primary school and consists of a number of tests, among others a reading test, an arithmetics test, an IQ-test and psychological tests that measure the presence of social-emotional problems.⁶

If the school decides that the pupil needs learning support it applies for additional money at a regional referral committee. The regional referral committee decides on the basis of the test results whether the pupil is eligible for Learning Support and thus whether the school will receive additional funding. A pupil is eligible if he is lagging behind in two of the following subjects: technical reading, reading comprehension, spelling and arithmetics and one of these subjects should be reading comprehension or arithmetic. In addition the pupil should have an IQ-score between 75 and 90.⁷ Pupils with an IQ-score between 91 and 120 can be eligible, provided they are lagging behind in two of the above mentioned subjects and have social-emotional problems (Dutch Educational Inspectorate, 2010).

On October 1, 2008 371,555 pupils were enrolled in pre-vocational secondary education and 98,930 pupils (27 percent) received Learning Support (Dutch Educational Inspectorate, 2010).

⁶The Ministry of Education decides which tests should be used to determine whether a pupil needs learning support.

⁷Data on IQ-scores are not saved in a database. It is therefore not possible to exploit this discontinuity in eligibility with the IQ score to estimate the effect of Learning Support on pupil achievement

The majority of the pupils with Learning Support were enrolled in the lowest two tracks of pre-vocational education.

Data

The analysis in this paper is based on register data from the Dutch Ministry of Education with exam results of all pupils that were enrolled in the final year of secondary education in 2008 or 2009. Since the majority of pupils with Learning Support (about 92 percent) is enrolled in the lowest two tracks of pre-vocational education, I use data on 107,241 pupils that were enrolled in the final year of the basic or advanced vocational track in 2008 or 2009. Of these pupils 2339 (2.2 percent) are dropped from the sample because they took the exam only in a subset of courses; did not have a complete exam record; or took the exam but did not attend courses at the school. In addition 1459 observations (1.4 percent) are dropped because information about the average income in the postal code area of residence of the pupil is missing.⁸

As will be explained in more detail in the next section, average neighborhood income will be used as monotone instrumental variable. Information about average personal income by postal code area is obtained from Statistics Netherlands and merged with the data set with exam results.⁹ Average personal income includes income from employment and from own business, income insurance benefits and social security payments. On January 1, 2009 there were 4015 postal code areas in the Netherlands with on average 4104 inhabitants.

The main outcome variable is the probability that a pupil passes the exam at the the end of pre-vocational education. This exam is important because a pupil can only enroll in secondary vocational education if he passes the exam. There are separate exams for the different sub-tracks

⁸Statistics Netherlands does not provide information about average personal income for postal code areas with less than 200 inhabitants.

⁹Statistics Netherlands measures average personal income by postal code area on a yearly basis. I take the average over the years 2008 and 2009 to create the variable average neighborhood income.

Table 1: Summary statistics

	Received Learning Support			No Learning Support		
	Mean	Stdev	N	Mean	Stdev	N
Basic vocational track						
Passed exam	0.953	0.212	27247	0.972	0.165	20902
Grade for math	6.319	1.429	21019	6.943	1.332	16729
Grade for Dutch language	6.236	0.950	27212	6.589	0.905	20844
Average neighborhood income*	20478	3135	27247	20635	3176	20902
Advanced vocational track						
Passed exam	0.930	0.256	11632	0.956	0.205	43662
Grade for math	5.800	1.484	9145	6.276	1.473	35229
Grade for Dutch language	5.843	1.041	11611	6.155	1.006	43551
Average neighborhood income*	20636	3165	11632	20827	3084	43662

*Average yearly personal income by postal code area in euro's.

and whether or not a pupil passes the exam depends on the average of the grades on the school exam and the central exam. The school exam is constructed by the school, with the quality monitored by the educational inspectorate, while the central exam is constructed by a national testing institute. A pupil passes the exam if he has a passing grade on all subjects, or when the pupil fails a maximum of two subjects but the grades for other subjects are high enough to compensate.¹⁰ Next to the probability of passing the exam I will investigate separately the effect of Learning Support on the test scores for math and the Dutch language at the central exam.¹¹ These test scores range from 1 to 10 and the pupil passes the test when he obtains a score of 5.5 or higher.

¹⁰A pupil passes the exam if the rounded average grade for each subject is a 6 or higher (on a scale from 1 to 10) For the advanced track both exams count for 50 percent of the final grade while for the basic track the school exam counts for 2/3 of the final grade. A pupil also passes the exam if he has one 5 while the other grades are 6 or higher, or when he has one 4/two times a 5 while the other grades are 6 or higher and at least one of the grades is a 7.

¹¹I will use the score at the first central exam as outcome variable. Pupils who fail at the first attempt can take a resit (about 3.5 percent of all pupils takes a resit). The scores on the resit are not

Table 1 shows summary statistics for pupils with and without Learning Support, separately for the basic and advanced vocational tracks. The majority, 56.6 percent, of the pupils in the basic track received Learning Support against 21 percent in the advanced vocational track. In both educational tracks pupils with Learning Support have on average lower grades for math and language and are less likely to pass the exam.

3 Empirical specification

The interest of this paper is in estimating the average causal effect of additional school resources for learning support on pupil’s exam results at the end of secondary education. This average treatment effect can be denoted in the following way

$$\Delta(0, 1) = E[y(t = 1)] - E[y(t = 0)] \tag{1}$$

where y is the exam result and t is the treatment variable which equals 1 to indicate receipt of Learning Support and 0 otherwise. This average treatment effect consists of the difference between two mean potential outcomes; the mean outcome we would observe if additional money for learning support would be spent on all pupils $E[y(t = 1)]$ and the mean outcome we would observe if no pupil would receive Learning Support $E[y(t = 0)]$. Estimation of the average treatment effect is complicated because the potential outcome $y(t = 1)$ is unobserved for individuals who did not receive Learning Support and the potential outcome $y(t = 0)$ is unobserved for individuals who received Learning Support. Using the law of iterated expectations, this identification problem can be highlighted by writing the first part of the average treatment effect as;

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

used in the analysis to make sure that the test results are from the same test for all pupils.

where z is the treatment actually received by the pupil. With a sample that contains information about exam results y , and information about the receipt of Learning Support for each pupil, the sampling process identifies the probabilities of receiving or not receiving treatment $P(z = 1)$, $P(z = 0)$ and the mean outcome for those that received treatment $E[y(t = 1)|z = 1] = E[y|z = 1]$. The sampling process does not identify the mean outcome that would be observed if those that did not receive treatment would have received the treatment. A similar reasoning holds for the second part of the average treatment effect $E[y(t = 0)]$.

Under the assumption that the treatment is exogenously assigned to pupils $E[y(t = 1)|z = 0] = E[y|z = 1]$ and $E[y(t = 0)|z = 1] = E[y|z = 0]$ and we can therefore obtain a point estimate of the average treatment effect by taking the difference in mean exam results between pupils with and without Learning Support ($\Delta(0, 1) = E[y|z = 1] - E[y|z = 0]$). This assumption is of course implausible because Learning Support is explicitly assigned to low-ability pupils. In the results section of this paper the point estimates obtained under the assumption of exogeneity will be shown as comparison with the other results and denoted by ETS (Exogenous Treatment Selection).

Instead of imposing an assumption that yields point identification I will use a different method to infer the causal effect of the additional school resources on exam results; a non-parametric bounds analysis. An influential paper by Manski (1989) showed that it is possible to identify bounds on the average treatment effect by using only the available data, without additional assumptions, if the support of the dependent variable is bounded. Substituting the unobserved potential outcomes with the minimum value of the outcome y_{min} gives lower bounds on $E[y(t = 1)]$ and $E[y(t = 0)]$, and replacing the unobserved potential outcomes by the maximum value of the outcome y_{max} gives upper bounds:

$$E[y|z = 1] \cdot P(z = 1) + y_{min} \cdot P(z = 0) \leq E[y(t = 1)] \leq E[y|z = 1] \cdot P(z = 1) + y_{max} \cdot P(z = 0) \quad (3)$$

$$E[y|z = 0] \cdot P(z = 0) + y_{min} \cdot P(z = 1) \leq E[y(t = 0)] \leq E[y|z = 0] \cdot P(z = 0) + y_{max} \cdot P(z = 1)$$

These worst-case bounds are interesting because they show what we can learn from data alone, they can however be quite wide. I will therefore layer nonparametric assumptions on the selection process and the treatment response function in order to tighten the bounds around the two mean potential outcomes. Upper (lower) bounds on the average treatment effect are subsequently obtained by subtracting the lower (upper) bound on $E[y(t = 0)]$ from the upper (lower) bound on $E[y(t = 1)]$.

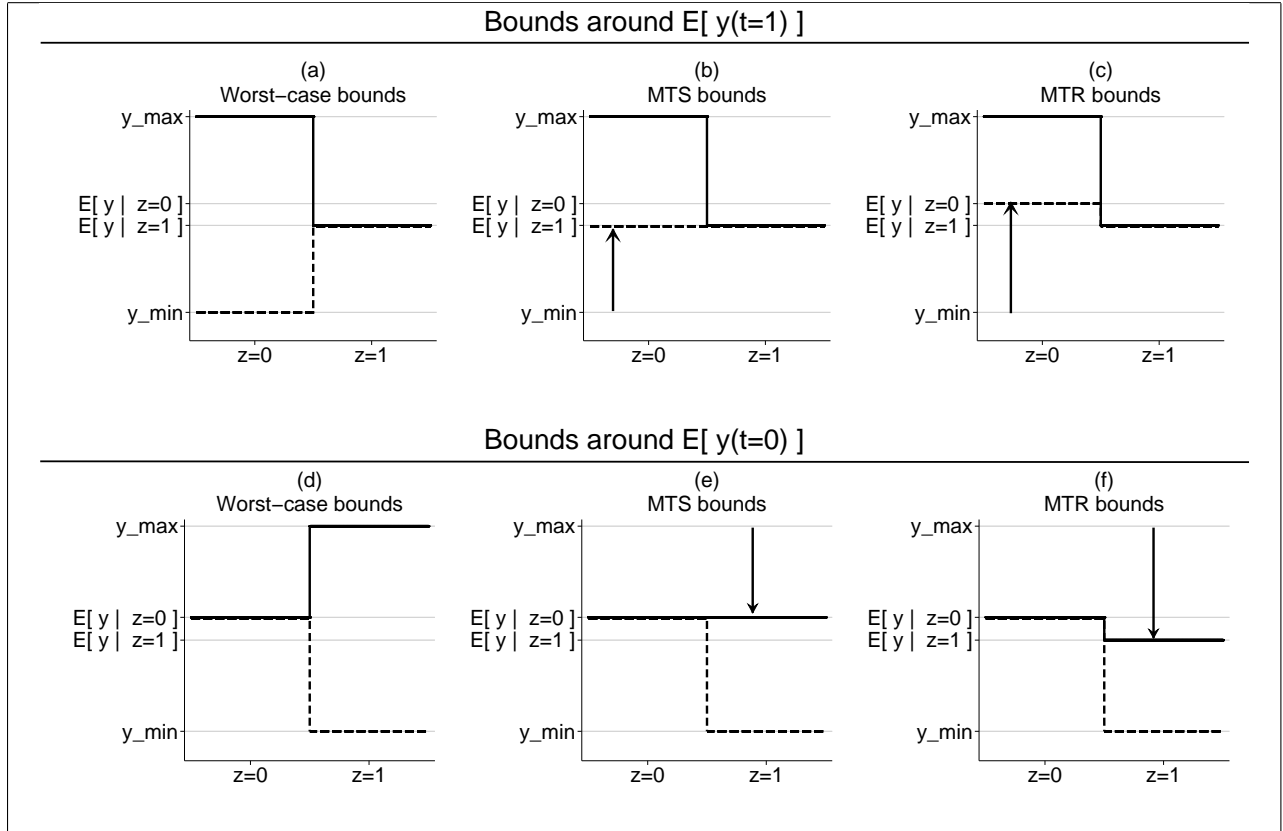
As explained in Section 2, only low-ability pupils, that are lagging behind in reading, spelling and/or arithmetics, receive Learning Support. The first assumption that will therefore be imposed is the monotone treatment selection assumption (Manski & Pepper, 2000):

$$E[y(t)|z = 1] \leq E[y(t)|z = 0] \quad (4)$$

The MTS assumption states that mean potential schooling outcomes are non-increasing in the actual receipt of Learning Support. It implies that if all pupils would receive the same treatment ($t = 1$ or $t = 0$), pupils currently assigned Learning Support ($z = 1$) will on average not perform better than pupils currently without Learning Support ($z = 0$).

Panels (b) and (e) of Figure 2 show how the MTS assumption can be used to tighten the bounds around the two mean potential outcomes. As is shown in panel (a) of Figure 2, the mean potential outcome of receiving treatment is observed for the pupils that actually received Learning Support ($z = 1$) and equals $E[y|z = 1]$. It is unobserved for pupils that did not receive Learning Support ($z = 0$) and without additional assumptions this can be anything between y_{min} and y_{max} . Under the MTS assumption the mean outcome we would observe for pupils that did not receive treatment in case they would receive treatment will not be lower than the

Figure 2: Graphical exposition of how MTS and MTR assumptions can tighten the bounds



mean outcome we observe for pupils that actually received Learning Support. $E[y|z = 1]$ can therefore be used as a lower bound. Under a similar reasoning $E[y|z = 0]$ can be used as an upper bound on the mean potential outcome of not receiving treatment for the pupils who received Learning Support, as is shown in panel (e). This gives the following MTS bounds:

$$E[y|z = 1] \leq E[y(t = 1)] \leq E[y|z = 1] \cdot P(z = 1) + y_{max} \cdot P(z = 0) \quad (5)$$

$$E[y|z = 0] \cdot P(z = 0) + y_{min} \cdot P(z = 1) \leq E[y(t = 0)] \leq E[y|z = 0]$$

In addition to the MTS assumption I will use a monotone instrumental variable (MIV) to tighten the bounds. If a data set contains not only information about realized treatments and outcomes but also about an additional variable v , it is possible to create sub-samples for

each value of v , and to obtain bounds on the mean potential outcomes within each of these sub-samples. If the upper and lower bounds vary over the sub-samples, this variation can be exploited if variable v satisfies the following monotone instrumental variable assumption (Manski & Pepper, 2000).

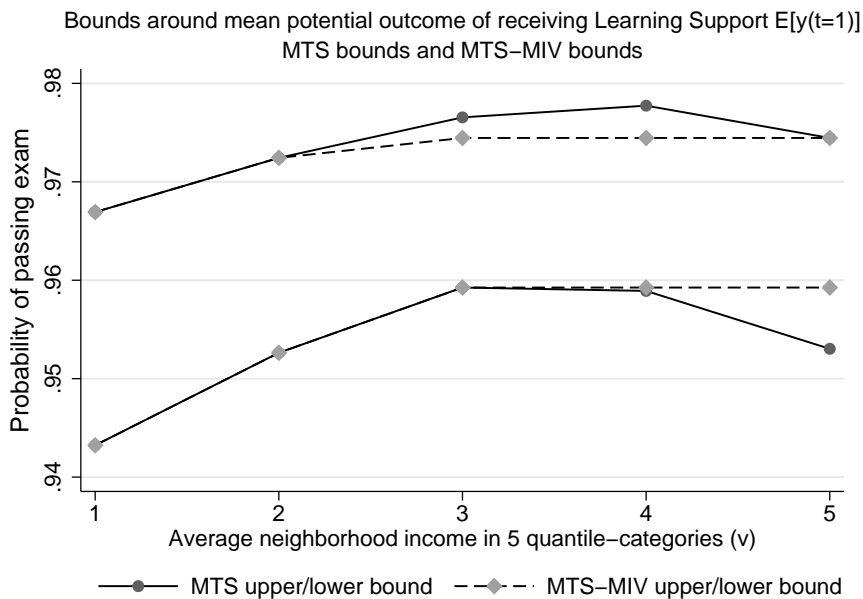
$$m_1 \leq m \leq m_2 \Rightarrow \tag{6}$$

$$E[y(t)|v = m_1] \leq E[y(t)|v = m] \leq E[y(t)|v = m_2], \quad t = 0, 1$$

Under this assumption the mean potential outcomes should be weakly increasing in the monotone instrument v . In contrast to an instrumental variable assumption, which imposes mean-independence, the monotone instrumental variable assumption allows for a weakly monotone positive relation between the variable v and mean potential schooling outcomes.

The monotone instrumental variable that will be used in this paper is average income in the neighborhood of residence of the pupil. Pupils living in a neighborhood with a high average income are more likely to have parents with a high income. Average neighborhood income is therefore a proxy for parental income and for the income of the pupil's neighbors. There is a extensive literature showing that there is a positive gradient between parental income and pupil's schooling outcomes (Haveman & Wolfe (1995)). In addition it is well-documented that children growing up in poor neighborhoods tend to have lower educational outcomes compared to children growing up in richer neighborhoods (Brooks-Gunn et al. (1993), Jencks & Mayer (1990)). Under the MIV assumption mean potential schooling outcomes should be non-decreasing in average neighborhood income. Average neighborhood income is thus allowed to have direct effect on pupil's exam results as long as this effect is not negative. In the analysis in this paper the monotone instrument v is a variable with average neighborhood income divided in 100 percentile

Figure 3: Graphical exposition of how the MIV assumption can tighten the bounds



categories, with about 500 observations per category by educational track.^{12,13}

From equation 6 it follows that $E[y(t=1)|v=m]$ is no lower than the lower bound on $E[y(t=1)|v=m_1]$ and it is no higher than the upper bound on $E[y(t=1)|v=m_2]$. For the sub-sample where v has the value m we can thus obtain a new lower bound on the mean potential outcome of receiving Learning Support, which is the largest lower bound over all the sub-samples where v 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 v higher than or equal to m .

Figure 3 shows an example where the black dots (connected by a solid line) are MTS lower and upper bounds for 5 quintile categories of neighborhood income estimated for the basic

¹²On average 482 observations per category for the basic track and 552 observations per category for the advanced track.

¹³Figure A in the appendix shows that the main results are not very sensitive to the number of categories of the MIV. The estimated upper and lower bounds hardly change if the number of categories is varied from 50 to above 100.

vocational track. If we focus on the sub-sample with $v = 4$ we can take the maximum lower bound over all sub-samples with a value of v lower or equal than 4. This is the lower bound at $v = 3$, so this becomes the MIV lower bound at $v = 4$. For the upper bound we can take the lowest upper bound over all values of $v \geq 4$. This turns out to be the upper bound at $v = 5$, so this becomes the MIV upper bound at $v = 4$. By repeating this for all values of v we get the MIV bounds which are shown by the gray diamonds (connected by the dashed line) in Figure 3. Equation 7 shows aggregate MIV bounds which are obtained by taking the weighted average of the MIV bounds over v .

$$\begin{aligned} \sum_{m \in M} P(v = m) \cdot [\max_{m_1 \leq m} LB_{E[y(t=1)|v=m_1]}] \\ \leq E[y(t = 1)] \leq \\ \sum_{m \in M} P(v = m) \cdot [\min_{m_2 \geq m} UB_{E[y(t=1)|v=m_2]}] \end{aligned} \tag{7}$$

Under the same reasoning we can obtain MIV-bounds around $E[y(t = 0)]$.

A final assumption that will be added is the monotone treatment response (MTR) assumption (Manski, 1997):

$$\begin{aligned} E[y(t = 1)|z = 0] &\geq E[y(t = 0)|z = 0] \\ E[y(t = 1)|z = 1] &\geq E[y(t = 0)|z = 1] \end{aligned} \tag{8}$$

Under this assumption pupil's exam results are on average non-decreasing in the conjunctural receipt of Learning Support. This implies that the additional school resources can have no effect or a positive effect but not a negative effect on pupil's mean schooling outcomes. Although this assumption is intuitive and it is difficult to think of reasons why increasing school resources would negatively affect pupil's schooling outcomes, it is not an uncontroversial assumption.¹⁴ As described in the Introduction most studies that investigate the effect of school resources find

¹⁴A potential reason for a negative impact of Learning Support is that pupils might be negatively affected from being stigmatized as a low-ability pupil if they receive Learning Support. The estimated lower bounds in Section 4, however, exclude a negative impact of Learning Support on the probability

a positive or zero impact on pupil outcomes, but there are also some studies that find negative point estimates. The MTR assumption will therefore be the last assumption that is layered on top of the other two nonparametric assumptions, such that it is possible to compare the bounds with and without the MTR assumption.

Panels (c) and (f) in Figure 2 show how the MTR assumption can be used to obtain tighter bounds around the two mean potential outcomes. The mean exam results that we would observe for the pupils without Learning Support if they would have received Learning Support will under the MTR assumption not be lower than the mean exam results we currently observe for these pupils. We can therefore use $E[y|z = 0]$ as a lower bound on the mean potential outcome of receiving treatment for the pupils with $z = 0$. For the pupils that received Learning Support we have under the MTR assumption that the mean exam results we will observe if they would not receive Learning Support will not be higher than the mean outcome we currently observe for these pupils. We can therefore use $E[y|z = 1]$ as an upper bound on the mean potential outcome of not receiving treatment for pupils with $z = 1$. This gives the following MTR bounds:

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

$$E[y|z = 0] \cdot P(z = 0) + y_{min} \cdot P(z = 1) \leq E[y(t = 0)] \leq E[y]$$

Combining the MTR and MTS assumptions gives the bounds which are shown in equation 10.

$$max \{E[y], E[y|z = 1]\} \leq E[y(t = 1)] \leq E[y|z = 1] \cdot P(z = 1) + y_{max} \cdot P(z = 0) \tag{10}$$

$$E[y|z = 0] \cdot P(z = 0) + y_{min} \cdot P(z = 1) \leq E[y(t = 0)] \leq min \{E[y], E[y|z = 0]\}$$

Computing these MTR-MTS bounds for each percentile category of average neighborhood income and applying equation 7 will give MTR-MTS-MIV bounds.

of passing the exam even without imposing the MTR assumption.

Estimation and inference

The above described bounds are estimated by plugging in sample means and empirical probabilities in the respective formula's for the bounds. As is described in Manski & Pepper (2000) and Manski & Pepper (2009) all bounds are consistent under the maintained assumptions, but the bounds using the MIV assumption may have finite-sample biases because these bounds are obtained by taking maxima and minima over collections of nonparametric regression estimates. Kreider & Pepper (2007) propose a bootstrap bias-correction method. They suggest to estimate the finite sample bias as $bias = \left(\frac{1}{K} \sum_{k=1}^K \theta_k \right) - \hat{\theta}$, where $\hat{\theta}$ is the initial estimate of the upper or lower bound and θ_k is the estimate of the k^{th} bootstrap replication. The bias-corrected MIV-bounds are subsequently obtained by subtracting the estimated biases from the estimated upper and lower bounds. Although the sample used in the analysis in this paper is large and finite sample bias is unlikely to be a significant issue, the MIV-bounds that will be shown in the results section are all bias-corrected using this method.

Confidence intervals around the bounds are obtained using the method from Imbens & Manski (2004). Equation 11 gives the formula for a 95-percent confidence interval:

$$CI_{0.95} = \left(\hat{lb} - c_{IM} \cdot \hat{\sigma}_{lb} \quad , \quad \hat{ub} + c_{IM} \cdot \hat{\sigma}_{ub} \right) \quad (11)$$

where \hat{lb} and \hat{ub} are the estimated upper and lower bounds and $\hat{\sigma}_{lb}$ and $\hat{\sigma}_{ub}$ are the estimated standard errors of the estimated lower and upper bounds, obtained by 1000 bootstrap replications. The parameter c_{IM} depends on the width of the bounds and is obtained by solving equation 12.^{15,16}

¹⁵For point identified parameters the Imbens-Manski confidence interval reduces to $CI_{0.95} = (\hat{\beta} \pm c_{IM} \cdot \hat{\sigma}_{\beta})$ with c_{IM} solving $\Phi(c_{IM}) - \Phi(-c_{IM}) = 0.95$.

¹⁶For the bounds that use the MIV assumption \hat{lb} and \hat{ub} in equations 11 and 12 are the bias-corrected upper and lower bounds.

$$\Phi \left(c_{IM} + \frac{(\hat{u}b - \hat{l}b)}{\max\{\hat{\sigma}_{lb}, \hat{\sigma}_{ub}\}} \right) - \Phi(-c_{IM}) = 0.95 \quad (12)$$

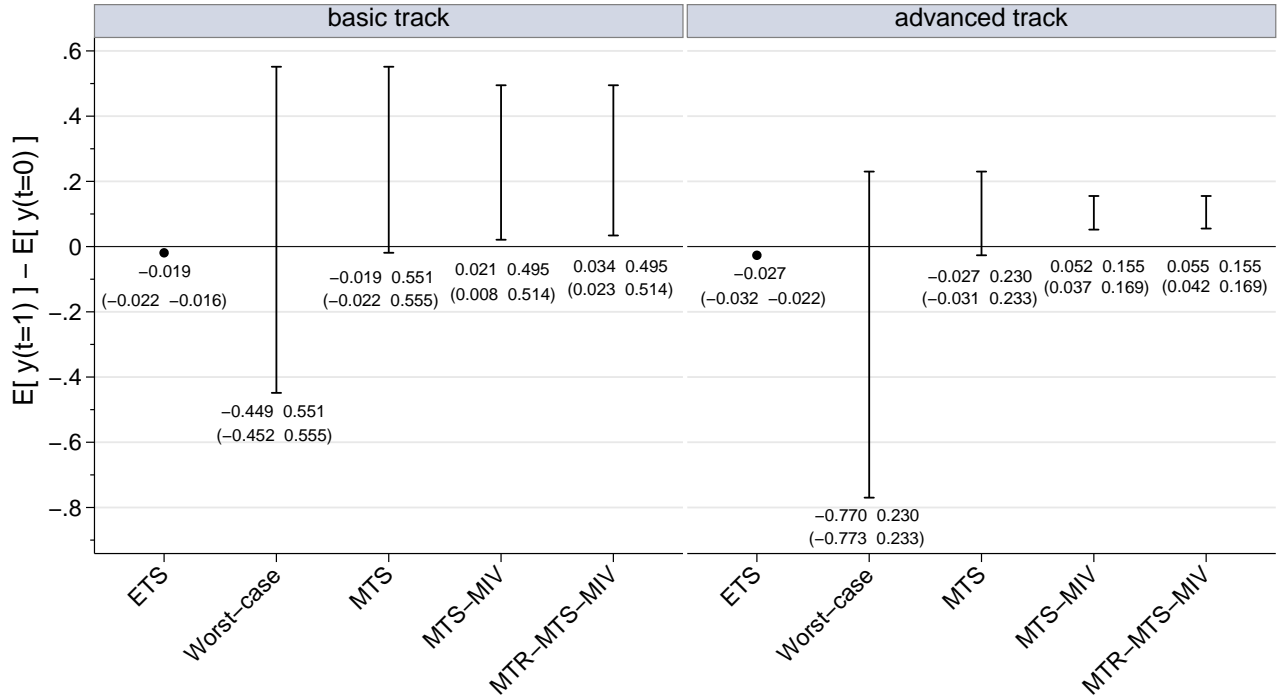
4 Results

Figure 4 shows nonparametric bounds around the effect of the additional funds for learning support on the probability that a pupil passes the exam at the end of pre-vocational education. Figure 4 also shows point estimates obtained under the assumption that Learning Support is exogenously assigned to pupils (ETS). The ETS estimates indicate that the effect is negative and significantly different from zero, for both educational tracks. These point estimates are likely biased downward due to the fact that Learning Support is explicitly assigned to low-ability pupils. The ETS results are therefore not informative about the causal effect of the additional funding for learning support, but they do show that pupils who received Learning Support are significantly less likely to pass their exam compared to pupils that did not receive Learning Support.

The worst-case bounds in Figure 4 show what we can conclude about the average treatment effect by using only the available data without imposing additional assumptions. Replacing the unobserved potential outcomes with the minimum (0) and maximum (1) probabilities of passing the exam gives bounds that show that the effect of the additional school resources is within [-0.45; 0.55] for the basic vocational track and within [-0.77; 0.23] for the advanced vocational track. These worst-case bounds are unfortunately rather wide and therefore not very informative. Adding the monotone treatment selection assumption significantly increases the lower bounds. Assuming that mean potential exam results are non-increasing in the actual receipt of Learning Support gives lower bounds equal to -0.02 for the basic track and -0.03 for the advanced track.

As was described in Section 3 it is possible to tighten the bounds by the use of a monotone

Figure 4: Effect of additional funds for learning support on probability that pupil passes exam

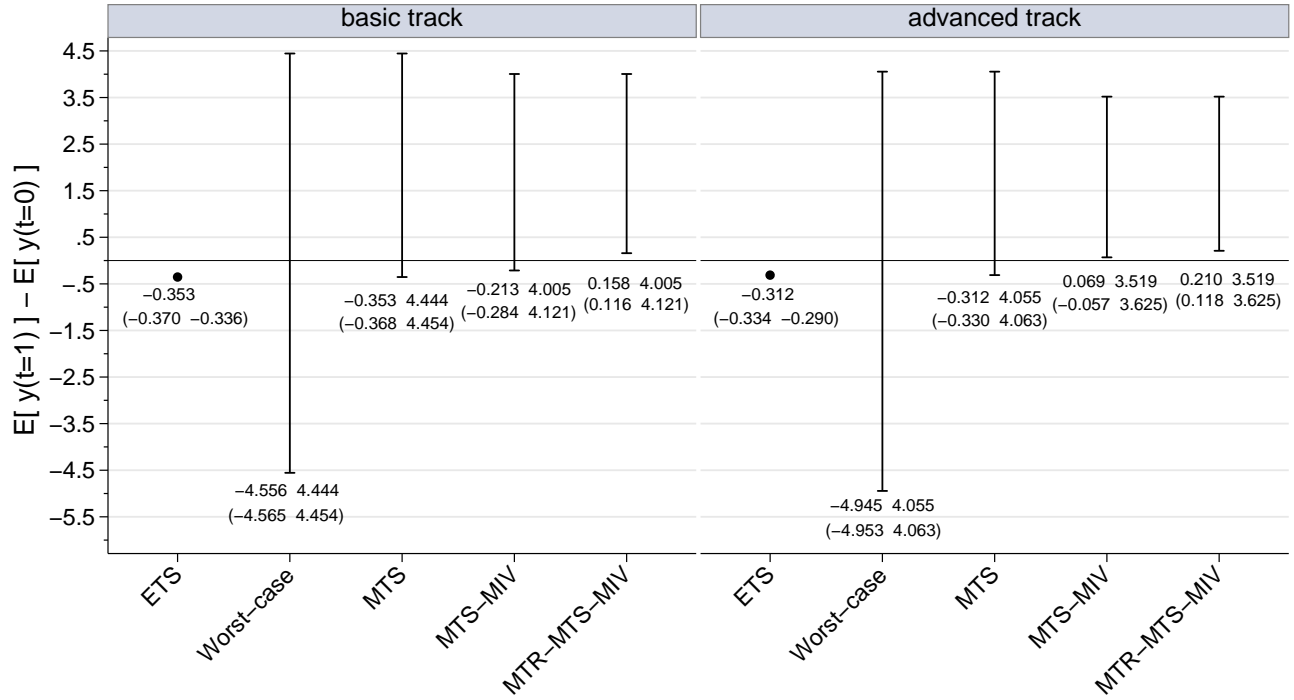


Note: Estimated bounds using the MIV assumption are bias-corrected using the bootstrap bias-correcting method proposed by Kreider & Pepper (2007). 95% conf. intervals (in parentheses) obtained using method from Imbens & Manski (2004) with 1000 bootstrap replications. Number of observations equals 48149 (basic track) and 55249 (advanced track).

instrumental variable. Using average neighborhood income as monotone instrumental variable affects both the lower and upper bounds and for the basic as well as the advanced track we obtain lower bounds that are positive and significantly different from zero. Combining the MTS and MIV assumptions gives bounds which show that the additional money for learning support increases the probability that a pupil passes the exam with at least 2.1 and at most 49.5 percentage points for the basic track and with at least 5.2 and at most 15.5 percentage points for the advanced track. These bounds do not only show that the effect of Learning Support is positive and significantly different from zero but they also exclude the naive point estimates obtained under the ETS assumption.

The tightest bounds in Figure 4 are obtained by combining the MTS and MIV assumptions

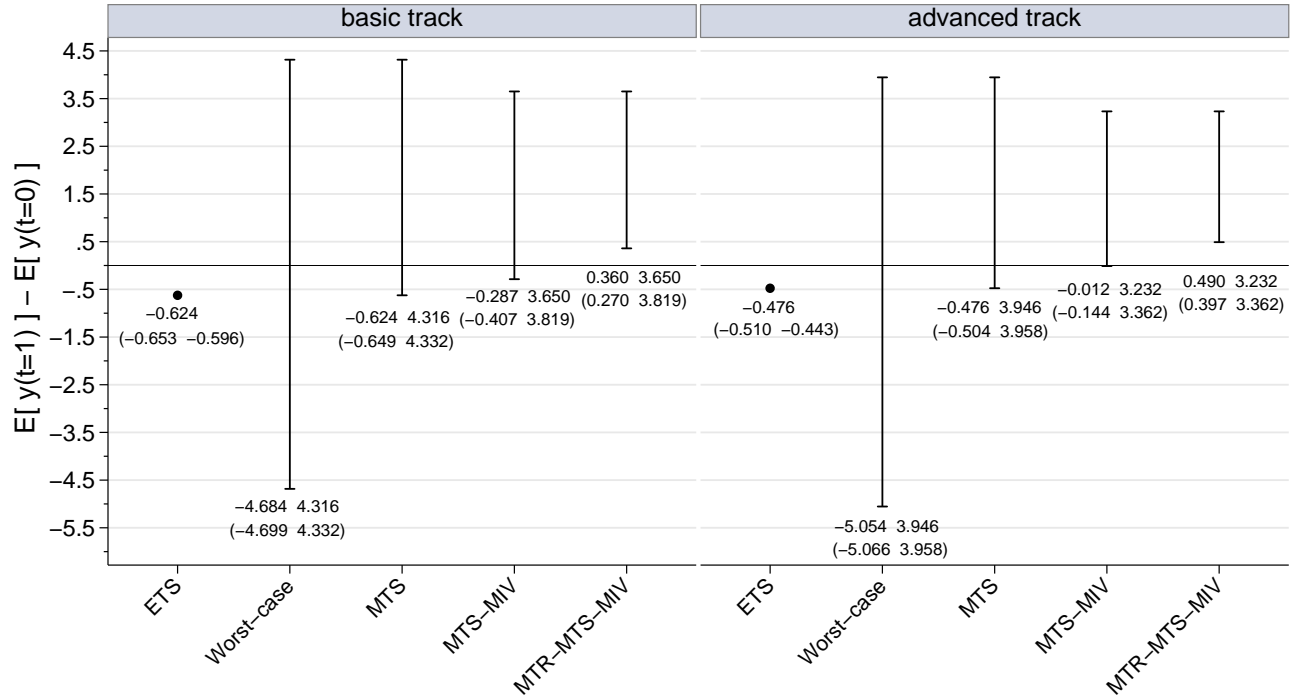
Figure 5: Effect of additional funds for learning support on language test score



Note: Estimated bounds using the MIV assumption are bias-corrected using the bootstrap bias-correcting method proposed by Kreider & Pepper (2007). 95% conf. intervals (in parentheses) obtained using method from Imbens & Manski (2004) with 1000 bootstrap replications. Number of observations equals 48056 (basic track) and 55162 (advanced track).

with the monotone treatment response assumption. Under the MTR assumption the additional funds for learning support will not lead to a decline in the probability that a pupil passes the exam. As pointed out in Section 3 this is a priori not an uncontroversial assumption. However, the bounds using only the MTS and MIV assumptions already exclude a negative impact of Learning Support, the MTR is therefore not a strong assumption in this application. Also the main conclusion that the additional school resources have a positive and significant effect on the probability of passing the exam does not rely on the MTR assumption. Combining the MTS and MIV assumptions with the MTR assumption gives somewhat tighter bounds which show that the additional school resources increase the probability of passing the exam by at least 3.4 percentage points for pupils in the basic track and by at least 5.5 percentage points for pupils

Figure 6: Effect of additional funds for learning support on math test score



Note: Estimated bounds using the MIV assumption are bias-corrected using the bootstrap bias-correcting method proposed by Kreider & Pepper (2007). 95% conf. intervals (in parentheses) obtained using method from Imbens & Manski (2004) with 1000 bootstrap replications. Number of observations equals 37748 (basic track) and 44347 (advanced track).

in the advanced track.

Since Learning Support is explicitly targeted at pupils who are lagging behind in reading, spelling and/or arithmetics at the moment they enroll in secondary education, it is relevant to see how Learning Support affects the exam results for math and language. Test scores at the exam range from 1 to 10 and a pupil obtains a passing grade for a subject if the score is a 5.5 or higher. Figure 5 shows bounds around the effect of Learning Support on the test score for the Dutch language at the central exam and Figure 6 shows the results for the test score for math at the central exam.

The results for test scores show a similar pattern as with the probability of passing the exam. The worst-case bounds are rather wide but the lower bounds increase substantially by adding

the monotone treatment selection assumption. Assuming that mean potential exam results are non-decreasing in average neighborhood income affects both the lower and upper bounds, and the most informative bounds around are obtained by combining the MTS, MIV and MTR assumptions. The tightest bounds show that the additional school resources increase language test scores by at least 16.7 percent of a standard deviation for the basic vocational track and by at least 20.6 percent of a standard deviation for the advanced vocational track.¹⁷ Lower bounds for math test scores are even higher and indicate that the additional funding increases math test scores with at least 25.3 percent of a standard deviation in the basic track and with at least 32.9 percent of a standard deviation in the advanced track.

5 Spillovers

In Section 3 the individual response function was denoted by $y(t)$ with y the exam result and t an indicator for whether the pupil received Learning Support. By writing the response function as $y(t)$ there is an implicit assumption, namely that of individualistic treatment response¹⁸ (Manski, forthcoming). Under this assumption the outcome of a pupil depends only on its own treatment and not on the treatment of other pupils. There might however be spillovers, for example if pupils without Learning Support can benefit from a remedial teacher that is hired in order to help pupils with Learning Support.

As described in Section 3 the interest of this paper is in the average treatment effect which consists of the difference between two mean potential outcomes; the mean outcome we would observe if additional money for learning support would be spent on all pupils and the mean outcome we would observe if no pupil would receive Learning Support. Let J indicate the population of pupils enrolled in the basic or advanced vocational track. The potential treatment

¹⁷Results in terms of percentages of a standard deviation are obtained by dividing the lower bounds by the standard deviations of the math test score (basic track: 1.421, advanced track: 1.487) and the language test score (basic track: 0.947, advanced track: 1.021).

¹⁸Also called the Stable Unit Treatment Value Assumption (SUTVA).

vector where all (no) pupils receive Learning Support is denoted by $t^J = 1^J$ ($t^J = 0^J$) and z^J is the vector specifying the treatments actually received by each pupil. Relaxing the assumption of individualistic treatment response and allowing the exam result of a pupil to depend on the treatments of all other pupils gives the following worst-case bounds:

$$\begin{aligned}
 y_{min} \cdot P(z^J \neq 1^J) + E[y|z^J = 1^J] \cdot P(z^J = 1^J) & \quad y_{min} \cdot P(z^J \neq 0^J) + E[y|z^J = 0^J] \cdot P(z^J = 0^J) \\
 \leq E[y(t^J = 1^J)] \leq & \quad \leq E[y(t^J = 0^J)] \leq \\
 y_{max} \cdot P(z^J \neq 1^J) + E[y|z^J = 1^J] \cdot P(z^J = 1^J) & \quad y_{max} \cdot P(z^J \neq 0^J) + E[y|z^J = 0^J] \cdot P(z^J = 0^J)
 \end{aligned} \tag{13}$$

Without additional assumptions the empirical evidence is not informative, since with unrestricted social interactions the upper bound on the mean potential outcome is y_{max} and the lower bound is y_{min} for each potential outcome vector that differs from the vector of realized treatments (Manski, forthcoming). In order to get informative bounds we need to impose some assumptions.

Potential spillovers could arise if pupils benefit from an increase in school performance of their peers that receive Learning Support. It might also happen that part of the additional money that the school receives is spent on school facilities that offer benefits to all pupils in the schools, for example a remedial teacher or school psychologist. Negative spillovers could potentially arise if the money that is spent on learning support for some pupils crowds out resources for other pupils. This is not an issue though, since the budget for Learning Support increases with the number of eligible pupils and this does not affect the amount spend on ineligible pupils. From 2005 to 2008 the number of pupils that received Learning Support has increased from 98665 to 101815 but this has not led to a reduction in the amount of money spend on ineligible pupils, nor in a reduction of the amount of money schools receive for each eligible pupil.¹⁹ I will therefore use the assumption of reinforcing interactions (RI) that states

¹⁹From 2005 to 2008, the per-pupil expenditure on a regular pupil increased from 6100 to 7100 and the per-pupil expenditure on pupils eligible for Learning Support increased from 10100 to 11100 (OCW (2006), OCW (2009)).

that potential exam results of a pupil are on average non-decreasing in his own treatment and in the treatment of other pupils. The assumption of reinforcing interactions was introduced in Manski (forthcoming) and is an extension of the monotone treatment response assumption. Under the assumption of reinforcing interactions the following should hold:

$$if \quad t^J \geq s^J \implies E[y(t^J)] \geq E[y(s^J)] \quad (14)$$

where $t^J \geq s^J$ implies that under treatment vector t^J all pupils get a treatment that is bigger than or equal to the treatment they receive under vector s^J .

For the potential treatment vector where all pupils get Learning Support we know that each pupil receives a treatment that is bigger than or equal to the treatment he currently receives ($1^J \geq z^J$). We can therefore use the observed mean exam results as a lower bound on $E[y(1^J)]$. Similarly, since by definition $0^J \leq z^J$ we can use the observed mean exam results as an upper bound on the mean potential outcome where no pupil receives Learning Support. This gives the following RI-bounds

$$E[y] \leq E[y(t^J = 1^J)] \leq y_{max} \quad (15)$$

$$y_{min} \leq E[y(t^J = 0^J)] \leq E[y]$$

To get tighter bounds we can add a monotone treatment selection assumption that states that the two mean potential outcomes are non-increasing in the actual receipt of Learning Support:

$$E[y(t^J = 1^J)|z = 1] \leq E[y(t^J = 1^J)|z = 0] \quad (16)$$

$$E[y(t^J = 0^J)|z = 1] \leq E[y(t^J = 0^J)|z = 0]$$

where z is a scalar indicating the treatment actually received by the pupil. Combining this assumption with the assumption of reinforcing interactions gives the following bounds.²⁰

²⁰By combining the assumption of reinforcing interactions with the monotone treatment selection assumption, the RI-assumption should hold both in the sub-sample with $z=1$ and in the sub-sample

$$\begin{aligned}
\max \{E[y|z = 1], E[y]\} &\leq E[y(t^J = 1^J)] \leq && y_{max} \\
y_{min} &\leq E[y(t^J = 0^J)] \leq \min \{E[y|z = 0], E[y]\}
\end{aligned}
\tag{17}$$

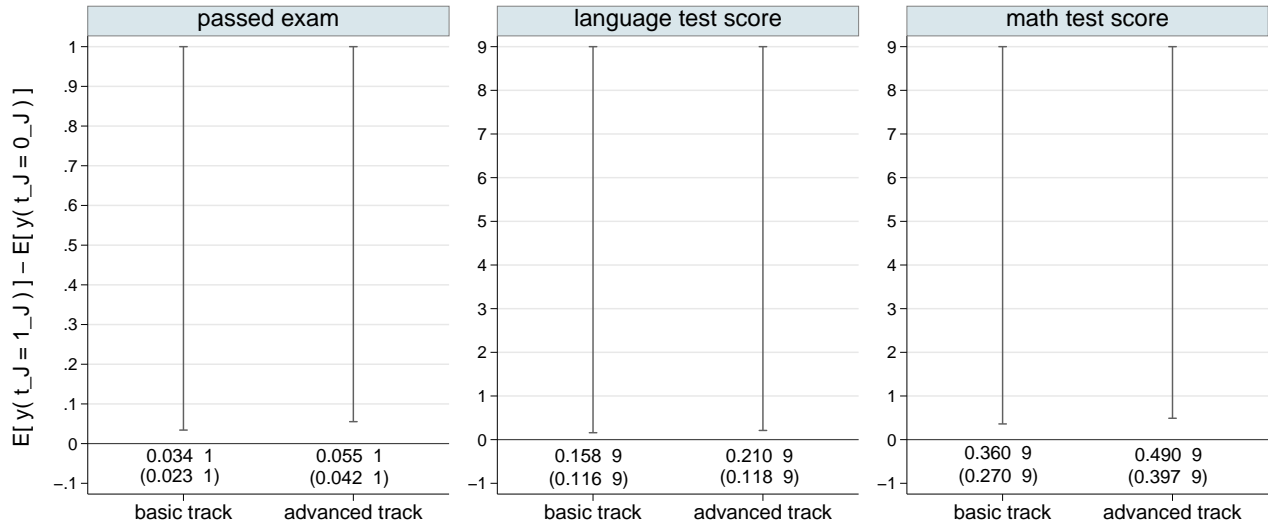
Computing the bounds in equation 17 for each percentile category of average neighborhood income and applying equation 7 will give RI-MTS-MIV bounds.

Figure 7 shows RI-MTS-MIV bounds around the effect of additional money for learning support on the probability of passing the exam and on math and language test scores. The lower bounds are all positive and significantly different from zero and show that additional money for learning support has a significant positive impact on the probability of passing the exam and on math and language test scores. These RI-MTS-MIV lower bounds are identical to the MTR-MTS-MIV lower bounds that were shown in Figures 4, 5, 6 where the assumption of individualistic treatment response was implicitly imposed. Allowing for positive spillovers gives however upper bounds which are a lot larger than the MTR-MTS-MIV upper bounds. This is due to the fact that the assumption of reinforcing interactions permits the possibility that if no pupil receives Learning Support all pupils obtain the minimum exam result (y_{min}) and it permits the possibility that if everyone receives Learning Support all pupils obtain the maximum exam result (y_{max}).

with $z=0$.

By using only the RI assumption within the two sub-samples defined by actual treatment status we have that $E[y(1^J)|z = \tau] \geq E[y(z^J)|z = \tau] = E[y|z = \tau]$ and $E[y(0^J)|z = \tau] \leq E[y(z^J)|z = \tau] = E[y|z = \tau]$ for $\tau = 0, 1$. If we add the MTS assumption from equation 16 we have that $E[y(1^J)|z = 0] \geq E[y(1^J)|z = 1] \geq E[y|z = 1]$ and $E[y(0^J)|z = 1] \leq E[y(0^J)|z = 0] \leq E[y|z = 0]$ which implies that $E[y(0^J)|z = 1] \leq \min\{E[y|z = 0], E[y|z = 1]\}$ and $E[y(1^J)|z = 0] \geq \max\{E[y|z = 0], E[y|z = 1]\}$. Taking the weighted average of the RI-MTS bounds on $E[y(1^J)|z = 1]$ and $E[y(1^J)|z = 0]$ and the weighted average of the RI-MTS bounds on $E[y(0^J)|z = 1]$ and $E[y(0^J)|z = 0]$ gives the RI-MTS bounds shown in equation 17.

Figure 7: RI-MTS-MIV bounds on the effect of additional funds for learning support



Note: Estimated bounds using the MIV assumption are bias-corrected using the bootstrap bias-correcting method proposed by Kreider & Pepper (2007). 95% conf. intervals (in parentheses) obtained using method from Imbens & Manski (2004) with 1000 bootstrap replications. Number of observations equals 48149 (basic track) and 55294 (advanced track) for passed exam; 48056 (basic track) and 55162 (advanced track) for language test score; 37748 (basic track) and 44374 (advanced track) for math test score.

6 Concluding remarks

Within the economics of education there are three highly debated issues: 1) whether increasing school resources has a positive impact on pupil achievement, 2) whether it is possible to increase schooling outcomes of pupils at the lower end of distribution, and 3) whether a high school intervention that affects pupils in their late childhood can be effective. This paper contributes to all three issues; it shows that a high school intervention that gives additional resources to schools in order to provide learning support to low-ability pupils significantly increases schooling outcomes.

Since 1999 the Dutch government gives secondary schools additional funding for each low-ability pupil that is enrolled in the school. School funding policies are difficult to evaluate, because they are often implemented nationwide and if there is variation in resources between schools this is generally correlated with (unobserved) school and pupil characteristics. This

paper overcomes the identification problem by using a nonparametric bounds analysis, that does not rely on the presence of exogenous variation in school resources and that obtains bounds around the average treatment effect also when the treatment effect differs between schools/pupils.

Layering relatively weak nonparametric assumptions gives bounds that show that the additional money for learning support increases the probability that a pupil passes the exam at the end of secondary education by at least 3.4 percentage points for pupils in the basic track and by at least 5.5 percentage points for pupils in the advanced track. Both math and language test scores increase significantly as a results of the additional school resources. The tightest bounds show that the additional funding for learning support increases language test scores by at least 16.7 (20.6) percent of a standard deviation and math test scores with at least 25.3 (32.9) percent of a standard deviation for pupils in the basic (advanced) vocational track. These conclusions do not change when I take potential spillovers into account.

The findings in this paper show that giving schools more resources, without putting specific restrictions on how to spend it, has a positive impact on pupil outcomes. This is an important finding, since governments can often not dictate schools how to spend their resources, while they can change the amount of resources given to schools. It could however be that certain ways of spending the resources are more effective than others. More research is therefore necessary to get a better understanding of the relative effectiveness of the different ways of spending resources on the provision of learning support.

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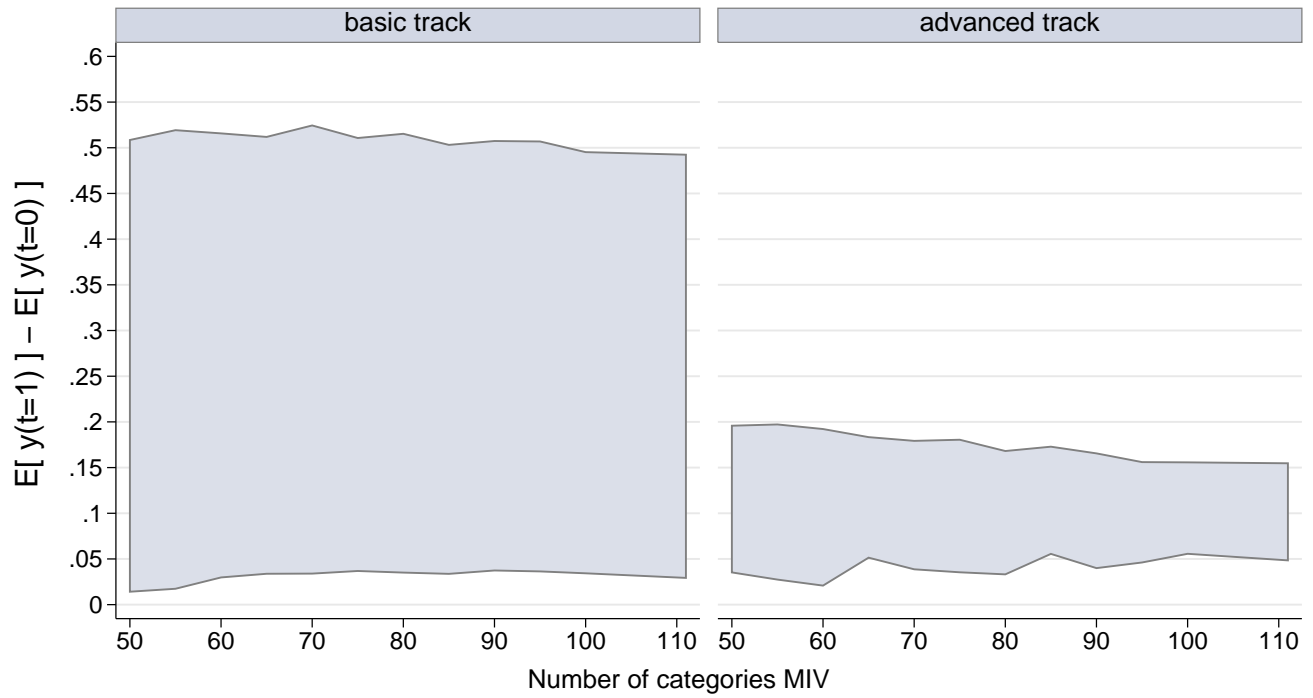
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Appendix

Figure A: MTR-MTS-MIV bounds on the effect of additional school resources on probability of passing exam by number of categories monotone instrumental variable



Note: Estimated bounds using the MIV assumption are bias-corrected using the bootstrap bias-correcting method proposed by Kreider and Pepper (2007). Number of observations equals 48149 (basic track) and 55249 (advanced track).