

# The effect of additional funds for low-ability pupils

## A nonparametric bounds analysis

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### 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 at the end of secondary education.

**JEL-codes:** I2, C14, C31.

**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.<sup>1</sup> 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.

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

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

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 taking potential spillovers into account.

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, when they are between 15 and 16 years old. Since only pupils with learning and/or behavioural 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 neighbourhood of residence of the pupil as a monotone instrumental variable, thereby assuming that pupils living in a poor neighbourhood will on average not have better potential educational outcomes than pupils living in a rich neighbourhood.

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.<sup>2</sup> There are however very few studies that investigate the causal effect of programs aimed at increasing schooling outcomes of pupils with learning difficulties.<sup>3</sup> The main reason for this gap in the literature is a lack of exogenous variation due to the non-random selection of pupils into remedial education programs. The results of this paper provide evidence that giving schools additional resources for low ability pupils can significantly improve pupil achievement. The estimated lower bounds 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 2.1 percentage points for pupils in the basic vocational track and by at least 5.2 percentage points for pupils in the advanced vocational track.

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

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<sup>2</sup>The 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)).

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

identification problem and the nonparametric bounds method. The results are shown in Section 4 and finally Section 5 summarizes and concludes.

## 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.<sup>4</sup> 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 education the pupil can enrol. School choice is free which implies that a pupil can enrol 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. The funding of a school thus depends on the number of enrolled pupils and the yearly per-pupil funding that a secondary school receives from the government is about 7100 Euro’s (Dutch Ministry of Education, 2009). Schools are not allowed to charge compulsory school fees, but they can ask parents for a voluntary contribution. This voluntary contribution is generally small and is used for extracurricular activities.

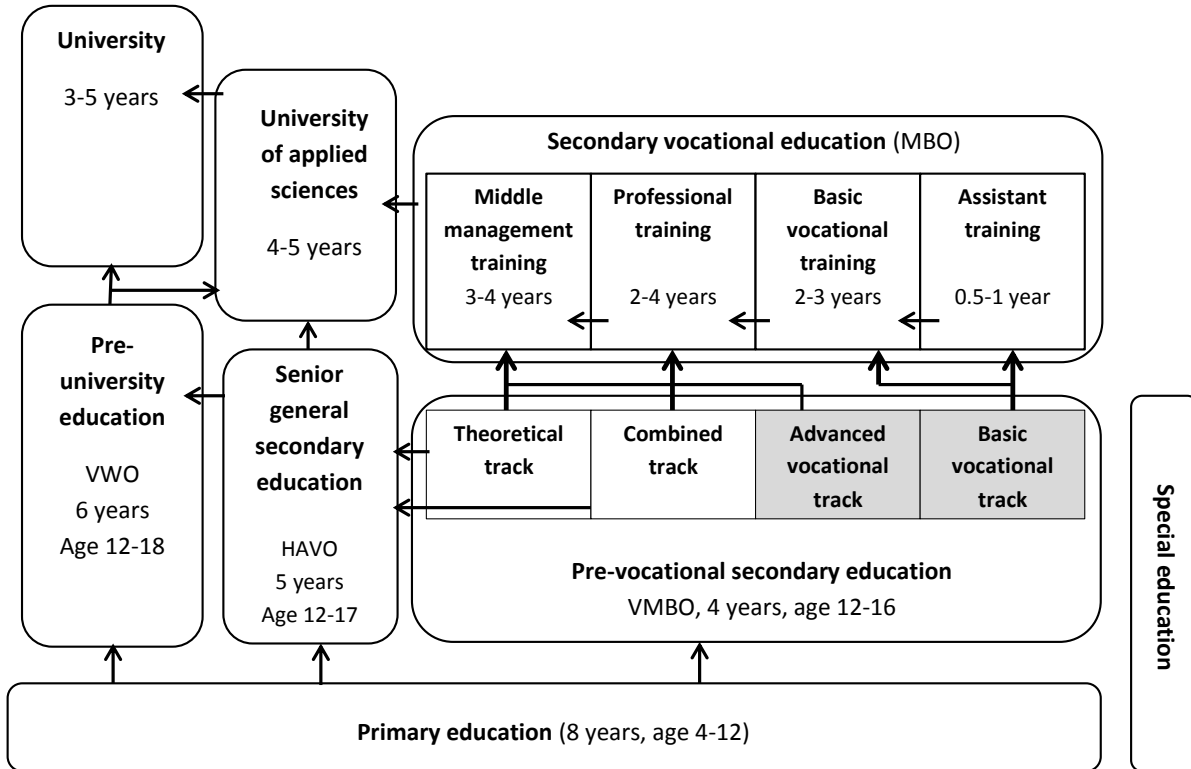
### Learning Support

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

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

Figure 1: Dutch educational system



each enrolled pupil with learning or behavioural difficulties.<sup>5</sup> The government spends about 11100 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 enrolment 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-

<sup>5</sup>This 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 thee 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.

emotional problems.<sup>6</sup>

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 arithmetics. In addition the pupil should have an IQ-score between 75 and 90.<sup>7</sup> 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). 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.<sup>8</sup>

As will be explained in more detail in the next section, average neighbourhood 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.<sup>9</sup> Average personal income includes income from employment and from

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

<sup>7</sup>Data 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.

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

<sup>9</sup>Statistics 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 neighbourhood income.

Table 1: Summary statistics

	Received Learning Support			No Learning Support		
	Mean	Stdev	N	Mean	Stdev	N
<b>Basic vocational track</b>						
Passed exam	0.953	0.212	27247	0.972	0.165	20902
Passing grade math	0.856	0.351	21037	0.927	0.260	16766
Passing grade Dutch language	0.951	0.216	27242	0.965	0.184	20886
Average neighbourhood income*	20478	3135	27247	20635	3176	20902
Gender (girl=1)	0.462	0.499	27247	0.404	0.491	20902
<b>Advanced vocational track</b>						
Passed exam	0.930	0.256	11632	0.956	0.205	43662
Passing grade math	0.705	0.456	9161	0.770	0.421	35306
Passing grade Dutch language	0.898	0.303	11630	0.932	0.251	43650
Average neighbourhood income*	20636	3165	11632	20827	3084	43662
Gender (girl=1)	0.538	0.499	11632	0.465	0.499	43662

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

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 end of pre-vocational education.<sup>10</sup> This exam is important because a pupil can only enrol in secondary vocational education if he passes the exam. There are separate exams for the different sub-tracks 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.<sup>11</sup>

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

<sup>10</sup>Almost all pupils (98.08%) in the final year of the basic and advanced vocational tracks take the exam. Exam taking is not significantly related to receipt of Learning Support, results are available upon request.

<sup>11</sup>A 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.

track. In both educational tracks pupils with Learning Support are less likely to pass the exam and are less likely to obtain a passing grade for math and the Dutch language.

### 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

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

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;

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

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  $E[y|z = 1]$ . 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  $E[y(t = 0)]$ .

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:

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

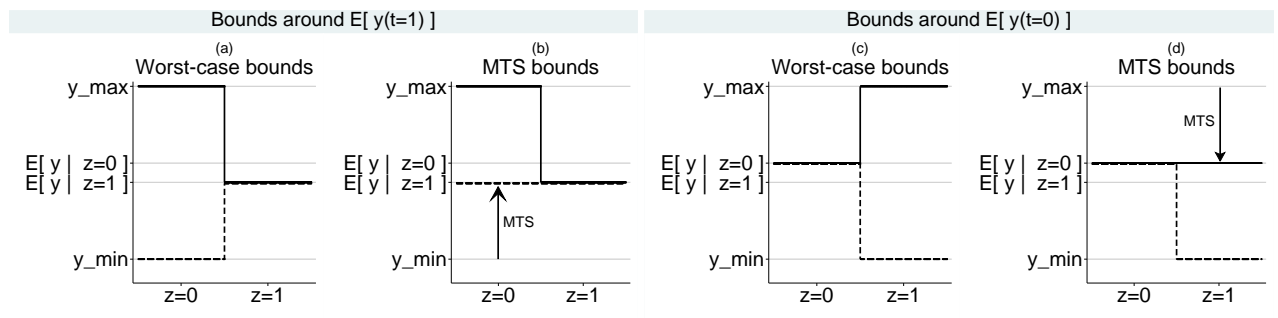
These worst-case bounds are interesting because they show what we can learn from data alone, they can however be quite wide. I will therefore layer nonparametric assumptions on the selection process and the treatment response function in order to tighten the bounds around the two mean potential outcomes. 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 (MTS)(Manski and Pepper, 2000):

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

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 ( $z = 0$ ).

Figure 2: Graphical exposition of how the MTS assumption can tighten the bounds



Panels (b) and (d) 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 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 (d). This gives the following MTS bounds:

$$\begin{aligned}
& E[y|z = 1] \\
& \leq E[y(t = 1)] \leq \\
& E[y|z = 1] \cdot P(z = 1) + y_{max} \cdot P(z = 0) \\
& \\
& E[y|z = 0] \cdot P(z = 0) + y_{min} \cdot P(z = 1) \\
& \leq E[y(t = 0)] \leq \\
& E[y|z = 0]
\end{aligned} \tag{5}$$

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 and 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 neighbourhood of residence of the pupil. Pupils living in a neighbourhood with a high average income are more likely to have parents with a high income. Average neighbourhood income is therefore a proxy for parental income and for the income of the pupil’s neighbours. There is a extensive literature showing that there is a positive gradient between parental income and pupil’s schooling outcomes (Haveman and Wolfe, 1995). In addition it is well-documented that children growing up in poor neighbourhoods tend to have lower educational outcomes compared to children growing up in richer neighbourhoods (Brooks-Gunn et al. (1993), Jencks and Mayer (1990)). Under the MIV assumption mean potential schooling outcomes should be non-decreasing in average neighbourhood income. Average neighbourhood 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 neighbourhood income divided in 100 percentile categories, with about 500 observations per category by educational track.<sup>12,13</sup>

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 neighbourhood income estimated for the basic 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 grey 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  $v$ .

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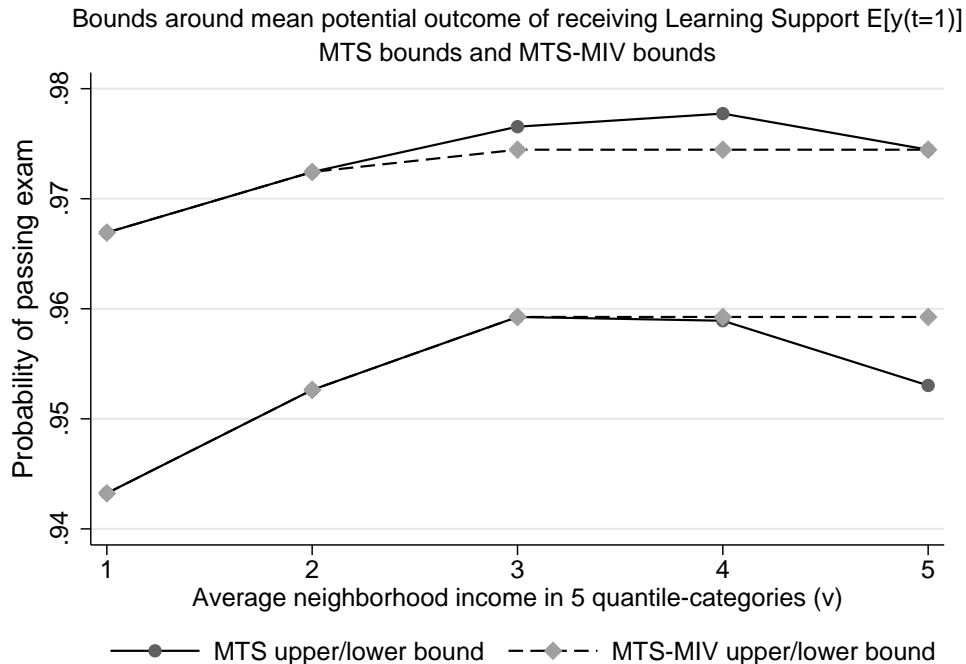
<sup>12</sup>On average 482 observations per category for the basic track and 552 observations per category for the advanced track.

<sup>13</sup>Figure A in Appendix A 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.

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

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

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



### 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 and Pepper (2000) and Manski and 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 and 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  $\theta_k$  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 and Manski (2004). Equation 8 gives the formula for a 95-percent confidence interval:

$$CI_{0.95} = \left( \hat{lb} - c_{IM} \cdot \hat{\sigma}_{lb} \quad , \quad \hat{ub} + c_{IM} \cdot \hat{\sigma}_{ub} \right) \quad (8)$$

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 9.<sup>14,15</sup>

$$\Phi \left( c_{IM} + \frac{(\hat{ub} - \hat{lb})}{\max \{ \hat{\sigma}_{lb}, \hat{\sigma}_{ub} \}} \right) - \Phi(-c_{IM}) = 0.95 \quad (9)$$

## 4 Results

### 4.1 The effect of additional funds for learning support on the probability of passing the exam

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 ( $ETS = E[y|z = 1] - E[y|z = 0]$ ). 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.

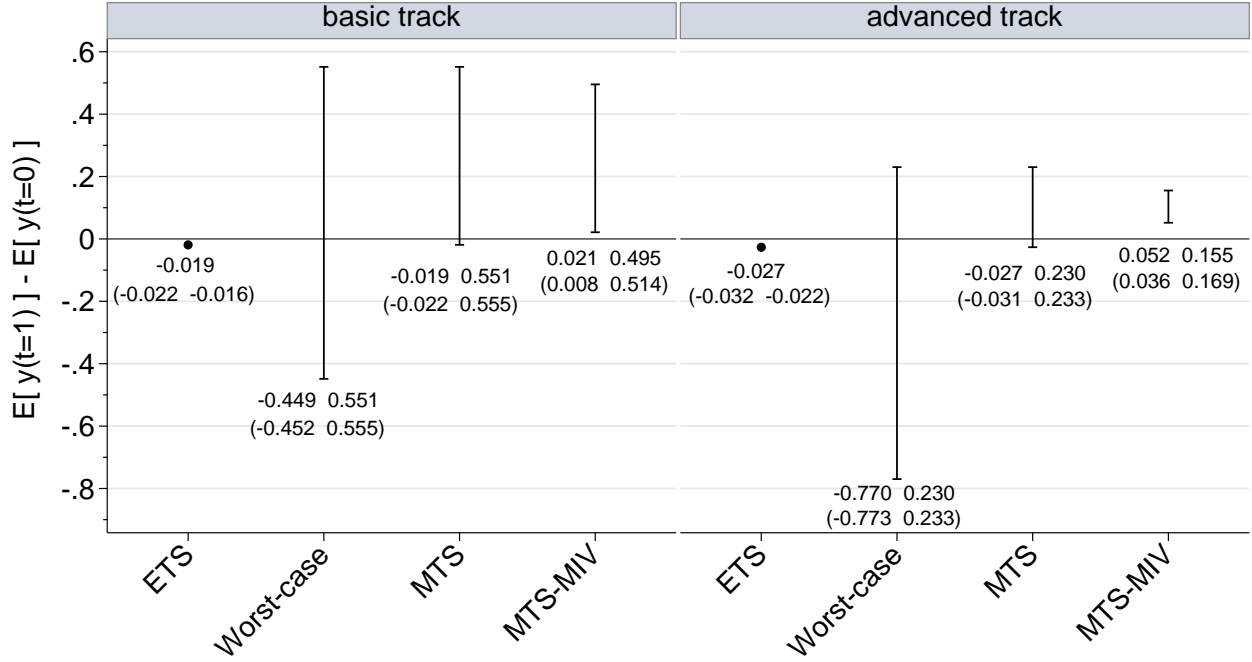
The worst-case bounds in Figure 4 show what we can conclude about the average treatment effect by using only the available data without imposing additional assumptions. Replacing the unobserved potential outcomes with the minimum (0) and maximum (1) probabilities

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<sup>14</sup>For 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  $\Phi(c_{IM}) - \Phi(-c_{IM}) = 0.95$ .

<sup>15</sup>For the bounds that use the MIV assumption  $\hat{lb}$  and  $\hat{ub}$  in equations 8 and 9 are the bias-corrected upper and lower bounds.

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



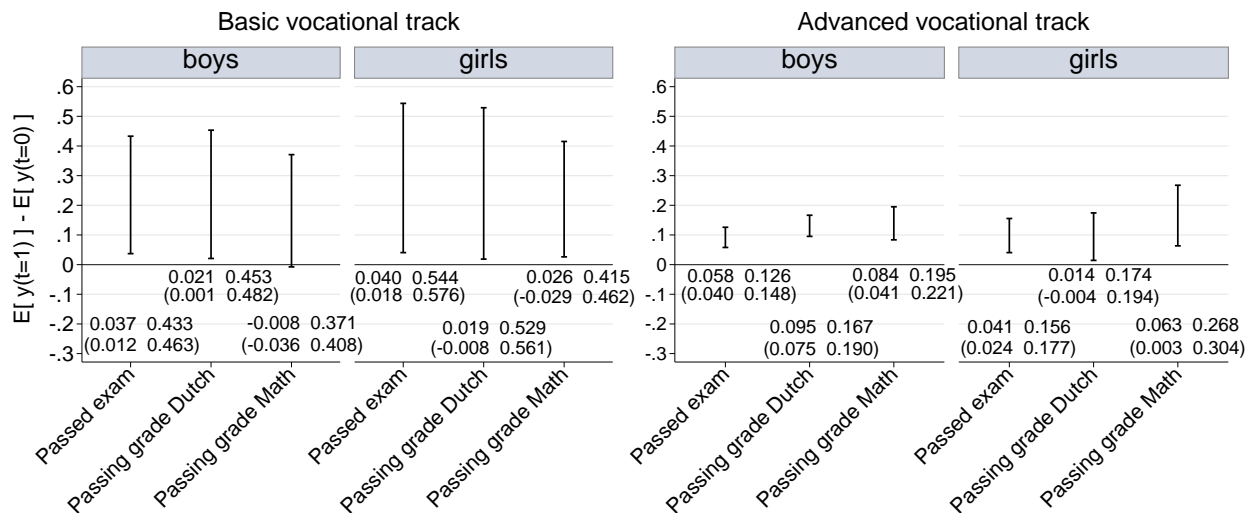
Note: Estimated bounds using the MIV assumption are bias-corrected using the bootstrap bias-correcting method proposed by Kreider and Pepper (2007). 95% conf. intervals (in parentheses) obtained using method from Imbens and Manski (2004) with 1000 bootstrap replications. Number of observations equals 48149 (basic track) and 55294 (advanced track).

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 instrumental variable. Using average neighbourhood 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

Figure 5: MTS-MIV bounds on the effect of additional funds for learning support by gender



*Note:* Estimated bounds are bias-corrected using the bootstrap bias-correcting method proposed by Kreider and Pepper (2007). 95% conf. intervals (in parentheses) obtained using method from Imbens and Manski (2004) with 1000 bootstrap replications. Number of observations equals 27113 (boys, basic track), 27100 (boys, language, basic track), 23852 (boys, math, basic track), 21036 (girls, basic track), 21028 (girls, language, basic track), 13951 (girls, math, basic track), 28721 (boys, advanced track), 28714 (boys, language, advanced track), 26019 (boys, math, advanced track), 26573 (girls, advanced track), 26566 (girls, language, advanced track), 18448 (girls, math, advanced track).

estimates obtained under the ETS assumption.

To see whether the results differ by gender, Figure 5 shows MTS-MIV bounds separately for boys and girls. In addition since Learning Support is explicitly targeted at pupils who are lagging behind in reading, spelling and/or arithmetics at the moment they enrol in secondary education, Figure 5 also shows whether Learning Support affects the probability of obtaining a passing grade for math and the Dutch 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 show that the results are very similar for boys and girls; for both genders the additional funding for learning support significantly increases the probability of passing the exam. If we compare the performance on the exams for math and language, we see that for boys the lower bounds for language are higher than the lower bounds for math, while for girls it is the opposite with the lower bounds for math being higher than the lower bounds for language. However, since the estimated bounds overlap it is not possible to conclude that the effect on the probability of obtaining a passing grade for math differs from effect on the probability of obtaining a passing grade for language.

## 4.2 Robustness checks

This section discusses the robustness of the main results presented in Figure 4 to modifications of the monotone instrument and to the presence of potential spillovers.

### Validity of the MIV assumption

Under the MIV assumption mean potential exam results should have a weak monotone positive relation with the 100 percentile categories of average neighbourhood income. Since mean potential exam results are not observed this assumption can't be tested. It is possible though to investigate whether the assumption is plausible by looking at schooling outcomes realized just before pupils start secondary education. At the end of primary education pupils in the Netherlands take a nationwide exit exam (the Cito test). Each year the Educational Inspectorate constructs a data set with the average exam scores of the primary schools in the Netherlands. By merging this data for the years 2008 and 2009 with the data on average neighbourhood income it is possible to check whether there is a monotone positive relation between average neighbourhood income and schooling outcomes observed just before pupils start secondary education.

Figure 6 shows a scatter plot and a local polynomial smooth of the relation between primary school average Cito test scores and average neighbourhood income.<sup>16</sup> The vertical lines indicate the 100 categories of the MIV. Figure 6 shows that primary school test scores show a monotone positive relation with average neighbourhood income, except for the very top and bottom end of the distribution. These nonmonotone parts are however likely due to the fact that there are very few data points at the top and bottom end of the distribution. In addition, the nonmonotone parts are within the top and bottom percentile categories and do therefore not violate the MIV assumption.<sup>17</sup> The bottom panel of Figure 6 shows again the relation between primary school test scores and average neighbourhood income, but now the 10 lowest and 10 highest income categories are excluded. The relation between average neighbourhood income and schooling outcomes at the end of primary school is now clearly monotone positive.

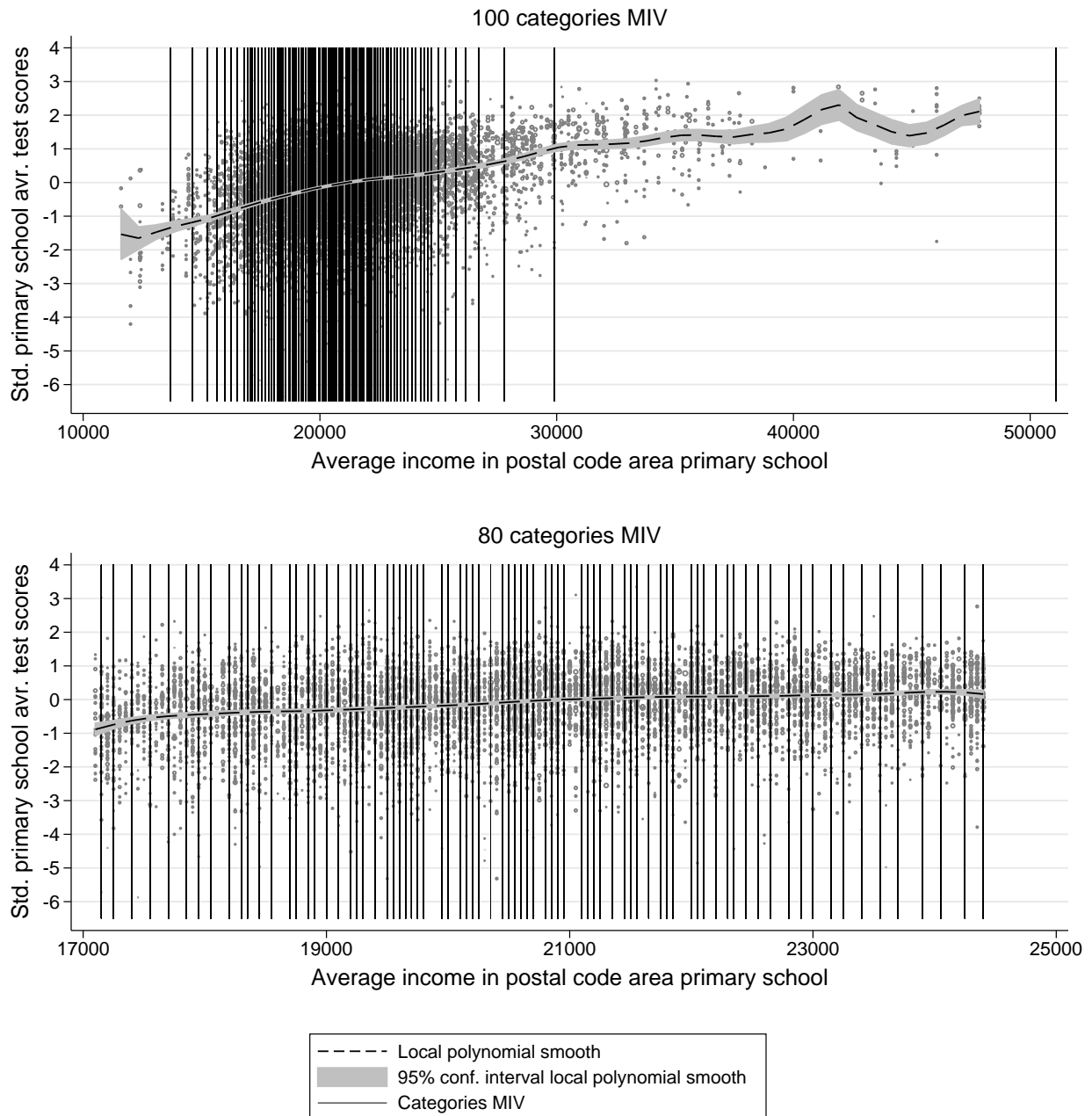
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<sup>16</sup>Average neighbourhood income is the average income in the postal code area in which the primary school is located. Although pupils often enrol in a secondary school outside the (4-digit) postal code area in which they live, this is not the case for the primary school, almost all pupils in primary school are enrolled in the school in their neighbourhood.

<sup>17</sup>The MIV assumption only requires that mean potential schooling outcomes of pupils in a percentile category of average neighbourhood income are weakly lower than the mean potential schooling outcomes of pupils in a higher percentile category of average neighbourhood income. If there is a nonmonotone relation between average neighbourhood income and mean potential schooling outcomes within a percentile category this does not violate the MIV assumption.



Figure 6: The relation between average neighborhood income and primary school test scores

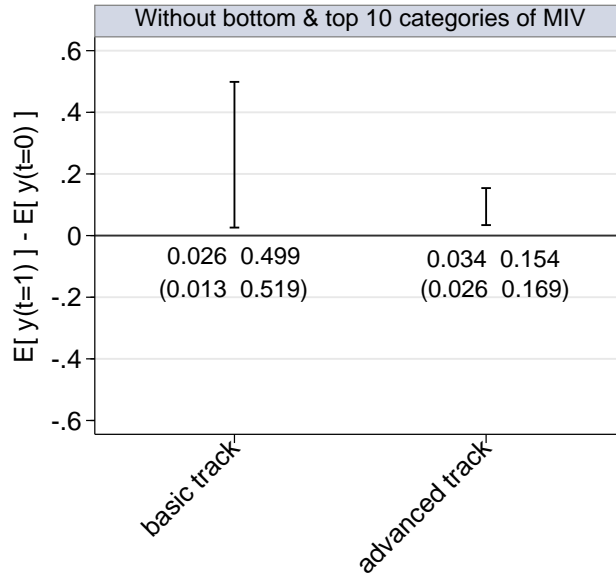


*Note:* The top panel is based on 10150 observations and the bottom panel is based on 7899 observations. The plots show Kernel-weighted (Epanechnikov) local 2nd order polynomial regressions of standardized primary school average test scores on average income in the postal code area in which the primary school is located. The ROT method is used to estimate the bandwidth. The school average test scores are weighted by the number of test takers in the school.

To check whether the main results in Figure 4 are sensitive to excluding the top and bottom end of the distribution of average neighbourhood income, Figure 7 show MTS-MIV

bounds on the effect of additional funding for learning support on the probability of passing the exam, excluding the 10 lowest and 10 highest categories of the MIV. The results are very similar to the results in Figure 4, showing that the results are not driven by potential nonmonotonicities in the top and bottom end of the distribution of average neighbourhood income.

Figure 7: MTS-MIV bounds on the effect of Learning Support on the probability of passing the exam, excluding the top and bottom 10 categories of the MIV



*Note:* Estimated bounds are bias-corrected using the bootstrap bias-correcting method proposed by Kreider and Pepper (2007). 95% conf. intervals (in parentheses) obtained using method from Imbens and Manski (2004) with 1000 bootstrap replications. Number of observations equals 38293 (basic track) and 44468 (advanced track).

## 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 response, also called the Stable Unit Treatment Value Assumption (SUTVA) (Manski, 2013). 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; pupils without Learning Support might benefit from the additional funding a school receives for pupils eligible for Learning Support. Relaxing the assumption of individualistic treatment response gives the response function  $y(t^J)$  with  $t^J$  the vector of potential treatments for all pupils in the basic or advanced vocational track.

When allowing for spillovers the definition of the average treatment effect is not so straightforward as in the case with individualistic treatment response. An natural way to extend the definition of the treatment to a setting that allows for spillovers is to define the treatment effect as 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 in the basic or advanced vocational track and the mean outcome we would observe if no pupil would receive Learning Support

$$E [y(t^J = 1^J)] - E [y(t^J = 0^J)]$$

If a school receives additional funding for pupils that are eligible for Learning Support, the school should use this additional funding to provide learning support for these eligible pupils. It might however be the case 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. Although low ability pupils might need and receive more inputs from teachers and school principals than high ability pupils, it is very unlikely that due to the additional funding for low ability pupils, high ability pupils receive even less inputs. Without Learning Support the low ability pupils would still be enrolled in the school, but the school would receive the same amount of funding for all pupils, which implies that the total amount of school resources will be lower. The assumption of individualistic treatment response is therefore replaced by the monotone spillover assumption (MSP)

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

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

The vector  $z^J$  specifies the treatments actually received by each of the pupils in the basic or advanced vocational track. The monotone spillover assumption states that the mean exam results of the ineligible pupils ( $z = 0$ ) in case no pupil would receive Learning Support, would not be higher than their current mean exam results. Similarly, MSP assumes that the mean exam results of pupils eligible for Learning Support ( $z = 1$ ) in case the schools would receive additional funding for all pupils, would not be lower than their current mean exam results, which are realized in a setting in which schools receive additional funding for only part of the pupils.<sup>18</sup> The MSP assumption thus allows for positive spillovers, but it rules out the possibility that there are negative spillovers, for example, due to the reallocation of teacher

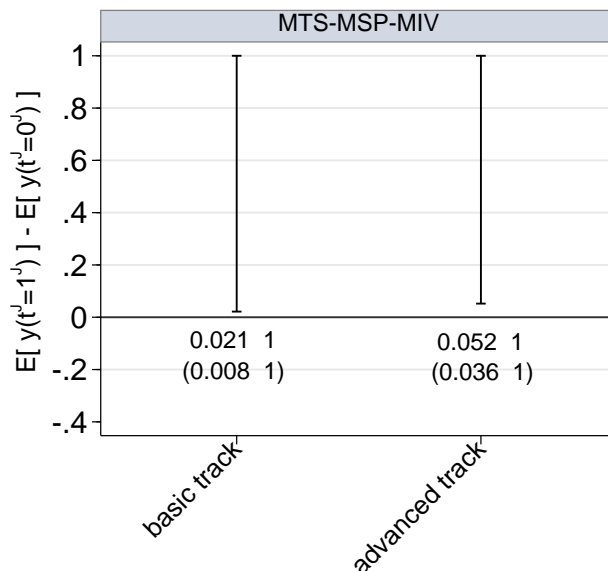
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<sup>18</sup>In contrast to the assumption of reinforcing interaction introduced in Manski (2013) the monotone spillover assumption assumes nothing about the direction of the treatment effect and is not an extension of the MTR assumption. The MSP assumption relaxes the individualistic treatment response assumption (SUTVA) to allow for monotone positive spillovers.

effort from pupils who currently receive Learning Support to those who do not, in case the school would receive additional funding for all pupils.

The MTS and MIV assumptions are easily extended to the case with spillovers. In Appendix B it is shown how the MSP, MTS and MIV assumptions can be combined to obtain bounds on the treatment effect. Figure 8 shows MTS-MSP-MIV bounds around the effect of additional funding for learning support on the probability of passing the exam. As can be seen in Figure 8 relaxing the assumption of individualistic treatment response to allow for monotone positive spillovers affects the upper bounds, but the lower bounds on the effect of additional funding for learning support are identical to the MTS-MIV lower bounds shown in Figure 4.

Figure 8: MTS-MSP-MIV bounds on the effect of additional funding for learning support on the probability of passing the exam



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

## 5 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 2.1 percentage points for pupils in the basic track and by at least 5.2 percentage points for pupils in the advanced 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.

## References

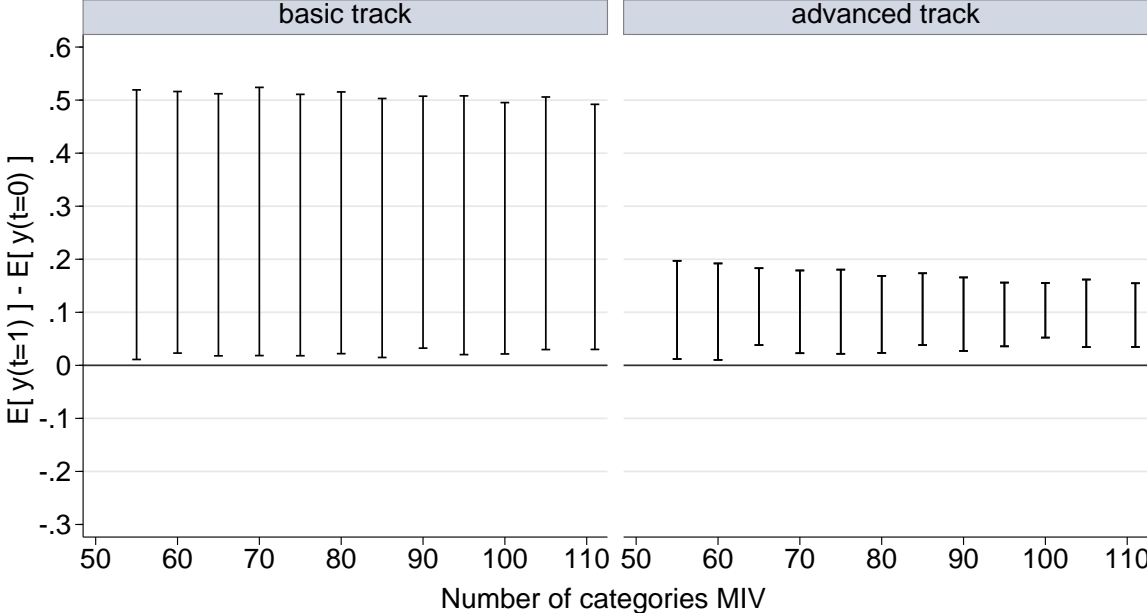
- Bénabou, R., Kramarz, F., and Prost, C. (2009). The french zones d'éducation prioritaire: Much ado about nothing? *Economics of Education Review*, vol. 28(3):pp. 345–356.
- Brooks-Gunn, J., Duncan, G., Klebanov, P., and Sealand, N. (1993). Do neighborhoods influence child and adolescent development? *American Journal of Sociology*, vol. 99(2):pp. 353–395.
- Dutch Educational Inspectorate (2010). *Onderwijs verslag 2008/2009*. Den Haag: Inspectie van het Onderwijs.
- Dutch Ministry of Education (2009). *Kerncijfers 2004-2008, Onderwijs Cultuur en Wetenschap*. Den Haag: Ministerie van OCW.

- Dutch Ministry of Education (2012). <http://www.rijksoverheid.nl/onderwerpen/voortgezet-onderwijs/vraag-en-antwoord/wat-is-leerwegondersteunend-onderwijs-lwoo.html>.
- European Council (2011). *Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions. Tackling early school leaving: A key contribution to the Europe 2020 Agenda*.
- Gibbons, S., McNally, S., and Viarengo, M. (2012). Does additional spending help urban schools? An evaluation using boundary discontinuities. *IZA discussion paper*, No. 6281.
- Hanushek, E. (2003). The failure of input-based schooling policies. *Economic Journal*, vol. 113(485):pp. F64–F98.
- Hanushek, E. (2006). School resources. In Hanushek, E. A. and Welch, F., editors, *Handbook of the Economics of Education*, volume 2, pages 865–908. Elsevier.
- Hanushek, E., Kain, J., and Rivkin, S. (2002). Inferring program effects for special populations: Does special education raise achievement for students with disabilities? *Review of Economics and Statistics*, vol. 84(4):pp. 584–599.
- Haveman, R. and Wolfe, B. (1995). The determinants of children’s attainments: A review of methods and findings. *Journal of Economic Literature*, vol. 33(4):pp. 1829–1878.
- Holmlund, H., McNally, S., and Viarengo, M. (2010). Does money matter for schools? *Economics of Education Review*, vol. 29(6):pp. 1154–1164.
- Imbens, G. and Manski, C. (2004). Confidence intervals for partially identified parameters. *Econometrica*, vol. 72(6):pp. 1845–1857.
- Jencks, C. and Mayer, S. (1990). The social consequences of growing up in a poor neighborhood. *Inner-city poverty in the United States*, :pp. 111–186.
- Kreider, B. and Pepper, J. (2007). Disability and employment. *Journal of the American Statistical Association*, vol. 102(478):pp. 432–441.
- Krueger, A. (2003). Economic considerations and class size. *Economic Journal*, vol. 113(485):pp. F34–F63.
- Lavy, V. and Schlosser, A. (2005). Targeted remedial education for underperforming teenagers: Costs and benefits. *Journal of Labor Economics*, vol. 23:pp. 839–874.

- Leuven, E., Lindahl, M., Oosterbeek, H., and Webbink, D. (2007). The effect of extra funding for disadvantaged pupils on achievement. *Review of Economics and Statistics*, vol. 89(4):pp. 721–736.
- Machin, S., McNally, S., and Meghir, C. (2010). Resources and standards in urban schools. *Journal of Human Capital*, vol. 4(4):pp. 365–393.
- Manski, C. (1989). Anatomy of the selection problem. *Journal of Human Resources*, 24(3).
- Manski, C. and Pepper, J. (2000). Monotone instrumental variables: With an application to the returns to schooling. *Econometrica*, vol. 68(4):pp. 997–1010.
- Manski, C. and Pepper, J. (2009). More on monotone instrumental variables. *The Econometrics Journal*, vol. 12:pp. S200–S216.
- Manski, C. F. (2013). Identification of treatment response with social interactions. *The Econometrics Journal*, vol. 16:pp. S1–S23.
- Papke, L. (2005). The effects of spending on test pass rates: evidence from Michigan. *Journal of Public Economics*, vol. 89(5):pp. 821–839.
- Van der Klaauw, W. (2008). Breaking the link between poverty and low student achievement: An evaluation of title I. *Journal of Econometrics*, vol. 142(2):pp. 731–756.

# Appendix A

Figure A: 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 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).

# Appendix B

This appendix shows how to combine the monotone spillover assumption with the MTS and MIV assumptions to obtain bounds around the treatment effect

$$E [y(t^J = 1^J)] - E [y(t^J = 0^J)] ,$$

where  $t^J$  is the vector of potential treatments for all pupils in the basic or advanced vocational track. The potential treatment vector where all (no) pupils receive Learning Support is denoted by  $t^J = 1^J$  ( $t^J = 0^J$ ). The treatment effect is 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 in the basic or advanced vocational track and the mean outcome we would observe if no pupil would receive Learning Support. Using the law of



iterated expectations we can write these two mean potential outcomes as

$$\begin{aligned}
E[y(t^J = 1^J)] &= E[y(t^J = 1^J)|z = 1] \cdot P(z = 1) + E[y(t^J = 1^J)|z = 0] \cdot P(z = 0) \\
E[y(t^J = 0^J)] &= E[y(t^J = 0^J)|z = 1] \cdot P(z = 1) + E[y(t^J = 0^J)|z = 0] \cdot P(z = 0)
\end{aligned} \tag{10}$$

with  $z$  a scalar indicating the treatment actually received by a pupil. Equation 11 shows the monotone spillover assumption (MSP)

$$\begin{aligned}
E[y(t^J = 1^J)|z = 1] &\geq E[y(t^J = z^J)|z = 1] = E[y|z = 1] \\
E[y(t^J = 0^J)|z = 0] &\leq E[y(t^J = z^J)|z = 0] = E[y|z = 0]
\end{aligned} \tag{11}$$

and equation 12 shows the MTS assumption

$$\begin{aligned}
E[y(t^J = 1^J)|z = 1] &\leq E[y(t^J = 1^J)|z = 0] \\
E[y(t^J = 0^J)|z = 1] &\leq E[y(t^J = 0^J)|z = 0]
\end{aligned} \tag{12}$$

The MSP and MTS assumptions imply the following bounds around the mean potential outcomes for  $t^J = 1^J$

$$\begin{aligned}
E[y|z = 1] &\stackrel{MSP}{\leq} E[y(t^J = 1^J)|z = 1] \leq y_{max} \\
E[y|z = 1] &\stackrel{MSP}{\leq} E[y(t^J = 1^J)|z = 1] \stackrel{MTS}{\leq} E[y(t^J = 1^J)|z = 0] \leq y_{max}
\end{aligned}$$

and the following bounds around the mean potential outcomes for  $t^J = 0^J$

$$\begin{aligned}
y_{min} &\leq E[y(t^J = 0^J)|z = 0] \stackrel{MSP}{\leq} E[y|z = 0] \\
y_{min} &\leq E[y(t^J = 0^J)|z = 1] \stackrel{MTS}{\leq} E[y(t^J = 0^J)|z = 0] \stackrel{MSP}{\leq} E[y|z = 0]
\end{aligned}$$

Substituting these upper and lower bounds into equation 10 gives the following MTS-MSP bounds around  $E[y(t^J = 1^J)]$  and  $E[y(t^J = 0^J)]$

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

The MTS and MSP assumptions can be combined with the MIV assumption using average neighbourhood income as monotone instrument

$$m_1 \leq m_2 \Rightarrow$$

$$E[y(t^J = 1^J)|v = m_1] \leq E[y(t^J = 1^J)|v = m_2] \quad (14)$$

$$E[y(t^J = 0^J)|v = m_1] \leq E[y(t^J = 0^J)|v = m_2]$$

Computing the bounds in equation 13 for each percentile category of average neighbourhood income and applying equation 15 will give MTS-MSP-MIV bounds on  $E[y(t^J = 1^J)]$ .

$$\begin{aligned} \sum_{m \in M} P(v = m) \cdot [\max_{m_1 \leq m} LB_{E[y(t^J = 1^J)|v = m_1]}] \\ \leq E[y(t^J = 1^J)] \leq \\ \sum_{m \in M} P(v = m) \cdot [\min_{m_2 \geq m} UB_{E[y(t^J = 1^J)|v = m_2]}] \end{aligned} \quad (15)$$

Under the same reasoning we can obtain MTS-MSP-MIV-bounds around  $E[y(t^J = 0^J)]$ . Upper (lower) bounds on the treatment effect are subsequently obtained by subtracting the lower (upper) bound on  $E[y(t^J = 0^J)]$  from the upper (lower) bound on  $E[y(t^J = 1^J)]$ .