Do Elite Schools Benefit Their Students?

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Abstract

This paper studies the effects of enrollment in an elite school on elite-school students' academic achievement in Hungary. Enrollment in a Hungarian elite school entails having academically stronger peers and early switching to a secondary school. We examine effects for elite-school students throughout the outcome distribution using a mild stochastic dominance assumption. We find that enrollment in an elite school decreases female and low-ability students' mathematics test scores two years after enrollment. However, these negative effects are short-lived, and we obtain estimates that are consistent with substantial positive effects four years after enrollment. School value-added estimates lie within our non-parametric bounds, and confirm the positive effects on the medium run.

Keywords: elite schools, partial identification, school effectiveness, selective education.

JEL-codes: C21, I21, I24, I26.

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1 Introduction

Most school districts feature *elite schools* in which admission is merit-based (i.e., depends on a qualifying priority score) and the student body consists of affluent, high-achieving students. Admission to these elite schools is highly selective and preparation for the admission requires substantial pecuniary and non-pecuniary resources from the parents of prospective students. Therefore, it is important for these parents to understand the extent to which their child may benefit from enrollment in an elite school.

A large literature studies the effectiveness of elite schools (for a recent summary, see Beuermann and Jackson, Forthcoming). This literature exploits discontinuities in admission chances that are created by the merit-based priority-score cutoffs. Thereby, these studies provide estimates for students who are on the margin of admission. However, if the effect of elite schools is heterogeneous, existing estimates may not be informative for parents, who would be interested in the effect for the *average* elite-school student with similar characteristics to theirs.

This paper studies the effects of elite schools on academic achievement in Hungary. Merit-based admission combined with high demand implies that elite-school students have high-achieving peers. Elite schools offer a more advanced, higher-paced curriculum, and teachers of high-qualification. Moreover, elite-school enrollment entails early switching to a secondary grammar school. Using administrative data, our study examines how enrollment in an elite school affects elite-school students' short- and medium-run academic achievement. Motivated by the potential heterogeneity in the effectiveness of elite schools, we conduct our analysis by gender and baseline ability (Oosterbeek et al., 2020).

Our main empirical strategy identifies the effects of enrollment in an elite school using non-parametric bounds. Our non-parametric bounds approach builds on a weak stochastic dominance assumption. We assume that conditional on observable student characteristics more able students are more likely to enroll in an elite school (conditional Monotone Treatment Selection, MTS; see Manski and Pepper, 2000; de Haan, 2011). The conditional MTS assumption yields an upper bound on the *average treatment effect on the treated* (ATET). We estimate the effect of elite-school enrollment throughout the outcome distribution, thus, we can study whether the effects differ between the top and the bottom end of the outcome distribution (de Haan and Leuven, 2020).

The non-parametric bounds approach offers several advantages. First, our approach identifies the effect of elite-school enrollment for elite-school students, and not only for students on the margin of admission. Second, the conditional MTS assumption is consistent with elite schools' admission policy and yields testable implications.

We find that enrollment in an elite school has a negative effect on female and low-ability elite-school students' mathematics test scores two years after enrollment. Elite-school enrollment reduces the probability of scoring above the median in mathematics by more than 7.5 percentage points, corresponding to 30 percent, for low-ability female students, and by more than 1 percentage points, corresponding to 10 percent, for low-ability male students. For high-ability female students, we find that elite-school enrollment reduces the probability of scoring in the top 10 percent in mathematics by more than 2 percentage points, corresponding to 10 percent. We argue that our findings for female and low-ability students are not the consequence of grading policies (e.g., ceiling effects, grading on a curve), but they reflect negative effects on skill formation. By contrast, we cannot rule out positive effects for high-ability male students at the upper half of the outcome distribution.

We next investigate whether the negative short-run effects persist four years after enrollment. We find that the upper bounds are positive and relatively large in magnitude for each ability and gender group. Thus, our non-parametric bounds strategy is uninformative about the sign of the effect on the medium run.

We further examine the medium-run effects of elite-school enrollment using a complementary empirical strategy. Using the selection on observables assumption, we estimate school value-added models to identify the average treatment effect on the treated. Our school value-added models control for students' lagged test scores and well as a rich set of student and school characteristics. We find that elite-school enrollment has a positive effect elite-school students' mathematics and reading test scores on the medium run. Even if the school value-added and non-parametric bounds empirical strategies build on different identifying assumptions, reassuringly, the school value-added estimates are always consistent with our non-parametric bounds on the effect of elite schools.

Our paper contributes to the understanding of the effectiveness of elite schools in a number of ways. First, numerous studies examine the effects of elite schools (or attending a better school) using regression discontinuity design (RDD) in settings where admission is merit-based (Jackson, 2010; Clark, 2010; Pop-Eleches and Urquiola, 2013; Bui et al., 2014; Lucas and Mbiti, 2014; Abdulkadiroglu et al., 2014; Dobbie and Fryer, 2014; Anderson et al., 2016; Barrow et al., Forthcoming).[1] These RDD estimates are informative for students who are on the margin of admission. Instead, our study focuses on the effect for the average student, and thus complements this literature. Moreover, these RDD studies have limited ability to identify heterogeneous effects by student ability, since student ability varies little at the margin of admission (Oosterbeek et al., 2020). By contrast, our identification strategy allows us to estimate the effect for different ability groups. When we split the sample by baseline ability, our estimates suggest that the benefits of elite schools are concentrated on high-ability students. When looking at the outcome distribution, our estimates indicate that the benefits of elite schools materialize at the top of the outcome distribution.

Second, our paper studies the effect of elite-school enrollment on outcomes that are measured in different points in time. Documenting how the effects of elite school enrollment change over time is important, since behavioral responses of students, teachers, or parents may materialize on different time horizons (Pop-Eleches and Urquiola, 2013). We show that elite-school enrollment has a negative effect on female and low-achieving students' mathematics score on the short run. This finding suggests that it more costly for certain groups of students to adjust to the elite-school environment.

Finally, we also contribute to the studies evaluating the performance of Hungarian elite schools. In the same context as ours, Horn (2013) finds positive, albeit, imprecisely estimated effects of selective secondary-school attendance on short-run academic achievement. Using less stringent identifying assumptions, our study considerably narrows the upper bound on these estimates.

The remainder of the paper is organized as follows. Section 2 provides background information about Hungarian education and the organization of elite schools. Section 3 describes

[1] A very much related literature studies elite-school effectiveness (or the effects of attending a better school) in settings where a lottery-based admission system is in place (e.g., Cullen et al., 2006; Deming, 2011; Dobbie and Fryer, 2011; Oosterbeek et al., 2020). Our study is similar to these papers in a sense that it identifies the effect of elite-school enrollment away from the priority-score cutoff. A key difference is that admission is merit-based in our setting, which implies that elite-school students are more selected that those who are admitted in a lottery-based admission system.

our data and provides summary statistics. Section 4 discusses our empirical strategies and presents the results of our validity checks. Section 5 presents our results. Section 6 concludes.

2 Context: Elite schools in Hungary

This section describes the institutional details of elite schools in Hungary. We describe admission to elite schools and detail the treatment.

Students begin primary education at age 6 in Hungary. After eight years in primary schools, they transition to secondary education. Secondary education is tracked in Hungary: students may choose a secondary grammar school, which has a more academic orientation and prepares students for higher education, or students may choose a vocational school, which has a less academic orientation and gives a vocational degree (see Table 1). Primary and secondary education are organized together in some schools. That is, in these *comprehensive schools*, students do not switch school when they transition from primary to secondary education. Even in these comprehensive schools, students are required to do the admission exam to proceed on the secondary track.

Primary-school students, at the end of grade 6, may decide to enroll in the 6-years long academic track of a secondary grammar school. We label these 6-years long academic tracks as *elite schools*. These elite schools are typically separate classes in a secondary grammar school, which have regular tracks as well. Thus, an elite school is essentially an "elite track" in a secondary grammar school (cf. Pop-Eleches and Urquiola, 2013).[2]

Admission to elite schools is merit-based. Elite schools organize admission exams where students have to solve numeracy and literacy tests. While all applicants solve the same test in the country, the priority-score formula used for the actual rankings is school-specific: it is a combination of the students' primary-school grades, the result of their written admission test, and the result of their oral admission exam. Since elite schools are highly oversubscribed, they are highly selective, and only high-achieving students are admitted.

Enrollment in an elite school is a composite treatment. First, elite-school students have

[2]Some of the secondary grammar schools offer a 8-years long academic track. Due to data limitations we do not study these 8-years long academic tracks, and drop students who enrolled in these 8-years long academic tracks from all of our samples.

Table 1: The overview of the education system in Hungary

Grade	1–4	5–6	7–8	9–12
Age	6–9	10-11	12–13	14–17
Path	Primary school			Regular track in a secondary grammar school
				Vocational school
			6-years long academic track in a secondary grammar school (elite school)	
		8-years long academic track in a secondary grammar school (excluded)		

Notes: The table provides an overview of the education system in Hungary. The regular and the 6-years long academic tracks take place in secondary grammar schools. We refer to the 6-years long academic track in a secondary grammar school as an elite school. We exclude the 8-years long academic track from our analysis.

academically stronger peers, which follows from the combination of merit-based admission and the high demand. Second, teachers in secondary schools are typically more qualified than primary school teachers, and they are more experienced with more mature students. Third, elite schools offer a more advanced, higher-paced curriculum. Finally, elite-school students switch school at age 12. By contrast, students who do not enroll in an elite school attend their primary school for an additional 2 years, and switch only at age 14.

3 Data and summary statistics

This section describes the data we use to estimate the effect of enrollment in an elite school on elite-school students' academic achievement. We begin, in Section 3.1, by describing the data and discussing the construction of our samples. In Section 3.2, we present summary statistics showing that elite-school students are positively selected based on socioeconomic status and academic achievement, and that the peer quality of elite-school students is better than those of non-elite-school students.

3.1 Data

For the analysis, we use administrative data from the National Assessment of Basic Competencies (NABC). Our data are longitudinal and cover every student in grades 6, 8, and 10 in the period of 2008–2014.

The backbone of our administrative data are the standardized test scores of the NABC.

The NABC is similar to OECD's Programme for International Student Assessment (PISA), but it extends to every student in grades 6, 8, and 10. The NABC (and the corresponding survey on students' background) is conducted annually in the last week of May. The NABC measures students' mathematics and reading skills. Students' 6th-grade test scores are measured on a scale, which has a mean of 1,500 and standard deviation of 200. In grades 8 and 10, the test scores are standardized in a way, such that the test scores are comparable over time (e.g., a student's 6th-grade and 8th-grade test scores are comparable) and across cohorts (e.g., the average test scores in grade 8 are comparable across cohorts). The standardized test scores differ from students' school-grades in many aspects: the standardized test scores are of low-stakes, they are graded blindly and externally, and they are not top-coded.[3]

Our data also include information on students' demographics (gender), socioeconomic status (the number of books at home, disadvantaged status, and parental education), and schools (school identifiers in grades 6, 8, and 10, school type, the county of the school, and the type of the settlement where the school is located). We also have rich information on students' academic achievement. Our data also include students' GPA in grade 5, i.e., one year prior the students' first NABC taking place. Finally, our data have information on students' 8th-grade mathematics grade.[4] These grades are given by students' own teachers and they are measured on a scale of 1 to 5.

We study two (overlapping) samples in order to maximize the power of our analysis. When studying short-run outcomes (i.e., outcomes measured 2 years after elite-school enrollment), we focus on students who we observe in grades 6 and 8. We refer to this sample as the *8th-grade sample*. The 8th-grade sample consists of five cohorts, whose 8th-grade outcomes are measured in the period of 2010–2014. When studying medium-run outcomes (i.e., outcomes measured 4 years after elite-school enrollment), we focus on students who we observe in grades 6, 8, and 10. We refer to this sample as the *10th-grade sample*. The 10th-grade sample consists of three cohorts, whose 10th-grade outcomes are measured in the period of 2012–2014.

In our analysis we make a number of sample restrictions to focus on students for whom

[3] Figure 3 presents the cumulative distribution function of students' 6th-grade mathematics and reading test scores.

[4] Information on students' socioeconomic status (number of books at home and parental education) and their school grades (5th-grade GPA and 8th-grade mathematics grade) is self-reported.

enrolling in an elite school is a viable option. First, we focus on students' with a complete academic path with no missing information. Second, our samples include students who are enrolled either in an elite or in a primary school in grade 8. Third, we focus on students whose propensity to enroll in an elite school is non-negligible. Therefore, our samples only include students (1) whose 5th-grade GPA is at least 4, (2) whose 6th-grade mathematics grade is at least 3, and (3) who attend a primary school in grade 6 from which at least one student enrolled in an elite school in our sample period. Appendix Table C1 provides information on the sample size reduction for each sample restriction. After the sample restrictions, we end up with about 25,000 students in each cohort (approximately 25% in each cohort).

In our analysis, we standardize students' test scores on our restricted samples. We conduct our analysis for four student groups, defined by (baseline) ability and gender, separately. We refer to students whose 6th-grade standardized test score is below the sample median as *low-ability students*, and whose 6th-grade standardized test score is above the sample median as *high-ability students*.

3.2 Summary statistics

Table 2 presents summary statistics of student characteristics by elite-school enrollment for each of our samples. Panel A focuses on students' pre-treatment characteristics. About 55 percent of the students are female. Approximately 37 percent of the students has maximum 150 books at home, 37 percent has between 150 and 600 books at home, and 27 percent has more than 600 books at home. On average, students' 5th-grade GPA is 4.6, on a scale of 1 to 5.[5] The composition of the 8th-grade and 10th-grade samples are almost identical.

Out of the 126,196 students in the 8th-grade sample, 16,702 students (13.2 percent) enrolled in an elite school. Students who enrolled in an elite school have higher socioeconomic status: about 45 percent of elite-school students has more than 600 books at home compared to 24 percent of those who did not enroll in an elite school. Elite-school students' 6th-grade mathematics (reading) test score is higher than the sample average by 53 (50) percent of a standard deviation. By contrast, students who did not enroll in an elite school have a 6th-

[5]The relatively high average 5th-grade GPA follows from the fact that our samples include students whose 5th-grade GPA is at least 4; see Section 3.1.

grade test score that is by 6 percent of a standard deviation lower than the sample average in both subjects. These patterns indicate that elite-school students are positively selected based on their socioeconomic status and (baseline) academic achievement.

Panel B of Table 2 reports summary statistics on students' outcomes. On average, students' 8th-grade mathematics grade is 4.0. Elite-school and non-elite-school students' average 8th-grade mathematics grades are similar. By contrast, elite-school students' 8th-grade standardized test scores are considerably higher than those of non-elite-school students. For example, elite-school students' average 8th-grade mathematics test score is 36 percent of a standard deviation higher the sample average. Non-elite-school students' average 8th-grade mathematics test score is 6 percent of a standard deviation lower than the sample average. Summary statistics of the 10th-grade sample indicate that elite-school students' average 10th-grade mathematics test score is 58 percent of a standard deviation higher the sample average. By contrast, non-elite-school students' average 10th-grade mathematics test score is 8 percent of a standard deviation lower than the sample average. These patterns indicate that the differences in standardized scores between elite-school and non-elite-school students persist up until 4 years after elite-school enrollment.

Table 2: Summary statistics

	8th-grade sample			10th-grade sample		
	Elite-school students (1)	Non-elite-school students (2)	Total (3)	Elite-school students (4)	Non-elite-school students (5)	Total (6)
A. *Pre-treatment characteristics*						
Female	0.54	0.56	0.55	0.54	0.56	0.55
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Max. 150 books at home	0.19	0.39	0.37	0.17	0.36	0.33
	(0.39)	(0.49)	(0.48)	(0.37)	(0.48)	(0.47)
B/w 150 and 600 books at home	0.36	0.37	0.37	0.34	0.37	0.37
	(0.48)	(0.48)	(0.48)	(0.47)	(0.48)	(0.48)
More than 600 books at home	0.45	0.24	0.27	0.49	0.27	0.30
	(0.50)	(0.43)	(0.44)	(0.50)	(0.45)	(0.46)
5th-grade GPA (1–5)	4.77	4.55	4.58	4.78	4.57	4.59
	(0.28)	(0.34)	(0.34)	(0.28)	(0.34)	(0.34)
6th-grade mathematics test score (std.)	0.53	-0.08	0.00	0.56	-0.08	0.00
	(1.01)	(0.97)	(1.00)	(1.02)	(0.97)	(1.00)
6th-grade reading test score (std.)	0.50	-0.08	0.00	0.51	-0.07	-0.00
	(0.96)	(0.98)	(1.00)	(0.96)	(0.99)	(1.00)
B. *Outcomes*						
8th-grade mathematics grade (1–5)	4.04	3.98	3.99	.	.	.
	(0.87)	(0.88)	(0.88)	(.)	(.)	(.)
8th-grade mathematics test score (std.)	0.36	-0.06	0.00	.	.	.
	(1.01)	(0.99)	(1.00)	(.)	(.)	(.)
8th-grade reading test score (std.)	0.42	-0.06	0.00	.	.	.
	(0.95)	(0.99)	(1.00)	(.)	(.)	(.)
10th-grade mathematics test score (std.)	.	.	.	0.58	-0.08	0.00
	(.)	(.)	(.)	(0.98)	(0.98)	(1.00)
10th-grade reading test score (std.)	.	.	.	0.53	-0.07	-0.00
	(.)	(.)	(.)	(0.91)	(0.99)	(1.00)
Number of students	16,702	109,494	126,196	8,850	63,112	71,962

Notes: The table presents the means and standard deviations of student characteristics for each sample. Columns (1) and (4) focus on students who did not enroll in an elite school, columns (2) and (5) focus on students who enrolled in an elite school, and columns (3) and (6) focus on the entire sample.

Figure 1 presents the distribution of students' *peer quality*, which is the leave-out mean of peers' 6th-grade standardized test scores within a school. The figure displays the distribution of peer quality before and after elite-school enrollment, i.e., in grades 6 and 8. We present these distributions for elite-school and non-elite-school students separately, and for students' 6th-grade mathematics and reading test scores.[6]

The left panels of Figure 1 show that the peer quality distribution of elite-school students shifts to the right between grades 6 and 8. The average 6th-grade mathematics test score of elite-school students' peers in grade 6 is 1,530. By contrast, the average 6th-grade mathematics test score of elite-school students' peers in the elite school is 1,671. Thus, elite-school students' peer quality substantially improves after they enroll in an elite school.

The right panels of Figure 1 show that the peer quality distribution of non-elite-school students largely remain unchanged between grades 6 and 8. The average 6th-grade mathematics test score of non-elite-school students' peers in grade 6 is 1,512 and it is 1,501 in grade 8. This small reduction in the peer quality of non-elite school students is consistent with positive selection into elite schools.[7] We also note that elite-school students' peer quality considerably exceeds the the peer quality of non-elite-school students in grade 8. Thus, enrollment in an elite school entails having academically stronger peers.

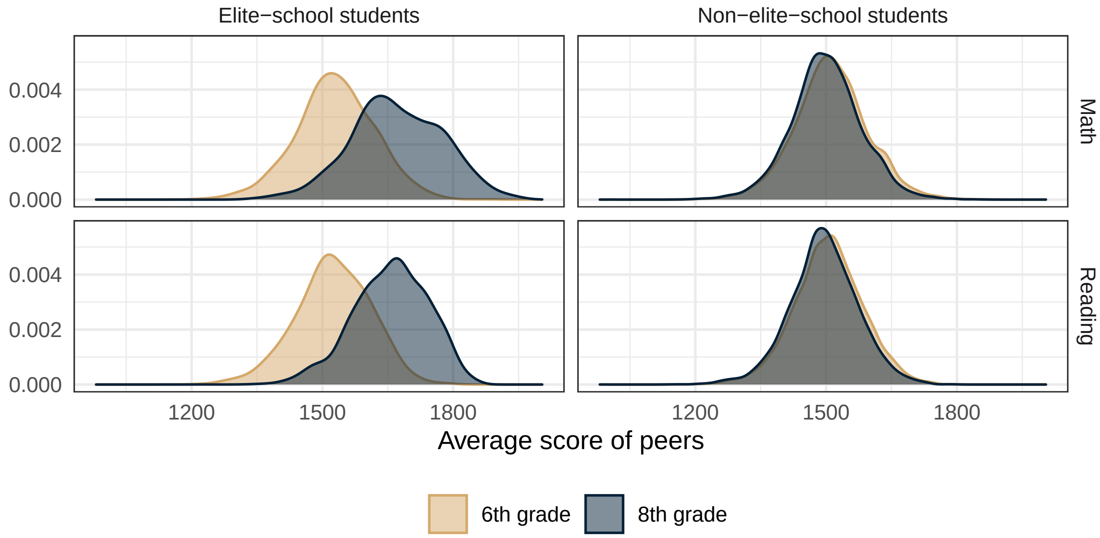
4 Empirical strategies

This section discusses our empirical strategies to identify the effect of enrollment in an elite school on the outcome distribution. We begin, in Section 4.1, by deriving a non-parametric bound on the effect of enrollment in an elite school using a weak stochastic dominance assumption (conditional Monotone Treatment Selection). In Section 4.2, we present evidence supporting the validity of our identifying assumption. Finally, in Section 4.3, we discuss a complementary empirical strategy that builds on the selection on observables assumption.

[6] When we compute students' peer quality, we include all students in the calculations. Therefore, in Figure 1, we preserve the original scale of students' 6th-grade standardized test scores; see Section 3.1.

[7] In the same context, Schiltz et al. (2019) show that the departure of smart peers to elite schools has a small, negative effect on the academic achievement of students who are left behind.

Figure 1: Peer quality and elite-school enrollment



Notes: The figure shows the distributions of students' peer quality in grades 6 and 8. Peer quality is the leave-out mean of peers' 6th-grade standardized test scores (within school). The left (right) panels focus on elite-school (non-elite-school) students. The top (bottom) panels focus on peers' 6th-grade mathematics (reading) test scores.

4.1 Non-parametric bounds: conditional MTS throughout the outcome distribution

We are interested in the effect of enrollment in an elite school on elite-school students' outcomes, that is, we focus on the the *average treatment effect on the treated* (ATET). We study the entire distribution of potential outcomes. Thus, the causal effect of interest, denoted by $\tau(\gamma)$, is the effect of elite-school enrollment on the probability of obtaining an outcome greater than γ for students who enrolled in an elite school:

$$\tau(\gamma) = \mathbb{P}\left[Y(1) \geq \gamma | D = 1\right] - \mathbb{P}\left[Y(0) \geq \gamma | D = 1\right],$$

where we denote student i's potential outcome by $Y_i(D)$ and D takes a value of one if the student enrolled in an elite school and zero otherwise.

The causal effect of interest focuses on students who enrolled in an elite school. This means that we identify the effect not only for students on the margin of admission, as studies that exploit priority-score cutoffs, but also for inframarginal students. Thus, we address whether elite schools academically benefit students who enrolled in them, and not whether the expansion of elite-school capacities benefits marginally admitted students.

The identification problem is that the potential untreated outcome distribution of students who enrolled in an elite school is unobservable. Therefore, we make an assumption on the selection of students into elite schools. Specifically, we impose a weak stochastic dominance condition on the potential untreated outcome distribution of students who enrolled in an elite school.

Assumption 1 (Monotone Treatment Selection, MTS)**.** The distribution of potential untreated outcomes of students who enrolled in an elite school weakly dominates that of those who did not enroll in an elite school:[8]

$$\mathbb{P}\left[Y(0) \geq \gamma | D=1\right] \geq \mathbb{P}\left[Y(0) \geq \gamma | D=0\right], \quad \forall \gamma. \tag{MTS}$$

The MTS assumption implies that the effect of enrollment in an elite school does not exceed the difference between the (observed) outcome distributions of students who enrolled in an elite school and of those who did not enroll:

$$\begin{aligned} \tau(\gamma) &= \mathbb{P}\left[Y(1) \geq \gamma | D=1\right] - \mathbb{P}\left[Y(0) \geq \gamma | D=1\right] \\ &\leq \mathbb{P}\left[Y(1) \geq \gamma | D=1\right] - \mathbb{P}\left[Y(0) \geq \gamma | D=0\right]. \end{aligned}$$

We further sharpen the upper bound on the effect of enrollment in an elite school by assuming that the MTS assumption holds for certain subgroups of students.

Assumption 2 (conditional MTS)**.** The distribution of potential untreated outcomes of students who enrolled in an elite school weakly dominates that of those who did not enroll in an elite school conditional on each values of the variable of X:

$$\mathbb{P}\left[Y(0) \geq \gamma | D=1, X\right] \geq \mathbb{P}\left[Y(0) \geq \gamma | D=0, X\right], \quad \forall \gamma. \tag{conditonal MTS}$$

[8]Our MTS assumption requires stochastic dominance of the potential outcome distributions, and thus is stronger than the MTS assumption originally proposed by Manski and Pepper (2000).

In the analysis, for a given value of γ, we use the conditional MTS assumption to derive bounds on $\mathbb{P}[Y(0) \leq \gamma | D = 1, X]$ for each values of X. We then combine these bounds to obtain an upper bound on the causal effect of interest:[9]

$$\tau(\gamma) \leq \sum_{x \in X} \left(\mathbb{P}[Y(0) \leq \gamma | D = 0, X = x] - \mathbb{P}[Y(1) \leq \gamma | D = 1, X = x] \right) \mathbb{P}[D = 1 | X = x] \quad \forall \gamma.$$

The upper bound on the effect of enrollment in an elite school equals to the corresponding exact matching estimator (Rubin, 1973). The exact matching estimator identifies the effect of enrollment in an elite school on the treated under the Conditional Independence Assumption (CIA). Instead of maintaining the CIA, we assume that selection into an elite school is positive conditional on X, and thus we identify an upper bound on the causal effect of interest.

We estimate the non-parametric bound on $\tau(\gamma)$ by the corresponding sample means and empirical probabilities. The 95% confidence intervals on the causal effect of interest are based on 1,000 bootstrap replications using the methodology derived by Imbens and Manski (2004).

We combine two pre-treatment variables, students' 5th-grade GPA and the number of books at home, to sharpen the bounds on the effect of enrollment in an elite school. We assume that conditional on students' 5th-grade GPA and the number of books at home the potential untreated outcome distribution of students who enrolled in an elite school weakly dominates of those who did not enroll in an elite school. Since admission to elite schools is merit-based, elite-school students are positively selected. Consistent with the merit-based admission procedure, we assume that positive selection is present even conditional on students' 5th-grade GPA, which is a pre-treatment proxy of students' academic ability, and the number of books at home, which is a proxy of socioeconomic status. The next section presents evidence using pre-treatment outcomes to support the validity of our identifying assumptions.[10]

[9] Since we investigate the effect of enrollment in an elite school on the entire outcome distribution, we could derive a *no-assumption* lower bound on $\tau(\gamma)$. This lower bound is, by construction, never positive, thus we do not report it.

[10] Students' 5th-grade GPA and the number of books at home are likely to be positively related to students' potential outcome distribution, and thus are valid monotone instrumental variables (MIVs) (Manski and Pepper, 2000; de Haan, 2011). We find empirical support for the combination of students' 5th-grade GPA and the number of books at home being valid MIVs. However, consistent with the argument of Richey (2016), the combination of the conditional MTS and MIV assumptions does not tighten our bounds.

4.2 Validity check

We next assess the validity of the conditional MTS assumption for the interaction of students' 5th-grade GPA and the number of books at home. A prerequisite of the conditional MTS assumption is a sufficient overlap between elite-school and non-elite-school students for each value of the interaction of students' 5th-grade GPA and the number of books at home (cf. Common Support Assumption). Moreover, if the conditional MTS assumption is met, then the distribution of elite-school students' pre-treatment outcomes should weakly dominate those of non-elite-school students' pre-treatment outcomes. We use students' 6th-grade standardized test score, which is realized prior to elite-school enrollment, to test this implication.

We first provide evidence supporting the overlap between elite-school and non-elite-school students' characteristics. Figure 2 presents the share of students who enrolled in an elite school for each value of the combination of 5h-grade GPA and the number of books at home. The figure splits the sample by (pre-treatment) ability and gender. There is no combination of 5th-grade GPA and the number of books at home such that the share of elite-school students is below 1 percent.[11]

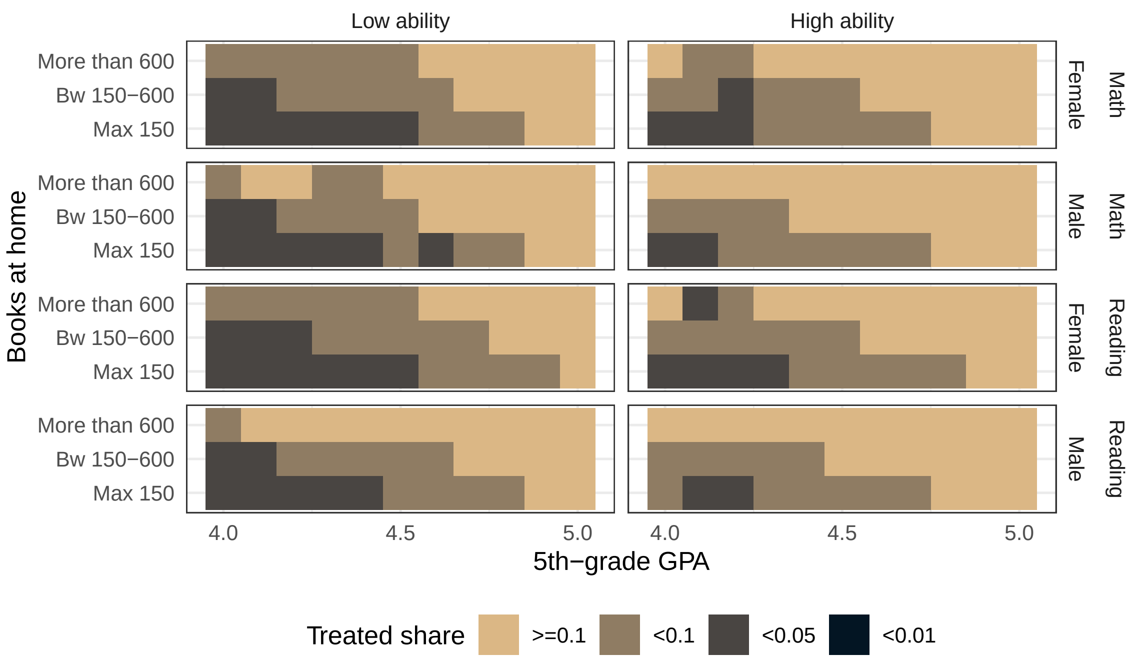
We next provide graphical evidence supporting the MTS assumption. Figure 3 displays the distribution of students' 6th-grade standardized test scores by elite-school enrollment and gender. The figure shows that the 6th-grade test score distribution of students who enrolled in an elite school weakly dominates of those who did not enroll for each gender and test type (mathematics and reading).

Figure 4 presents a formal test of the validity of the conditional MTS assumption. For each value of the combination of students' 5th-grade GPA and the number of books at home, we perform a one-sided Kolgomorov-Smirnov test. Figure 4 presents the corresponding p-values of the Kolgomorov-Smirnov test by gender and pre-treatment ability for each value of the combination of 5th-grade GPA and number of books at home. Out of the 264 tests we perform, we reject the null hypothesis only 6 times at a 10 percent significance level. We interpret these results as strong evidence supporting the validity of the conditional MTS assumption.[12]

[11] Appendix Figure A1 provides the same information for the 10th-grade sample, with the same conclusion.

[12] Appendix Figure A2 provides evidence supporting the validity of the conditional MTS assumption for the 10th-grade sample.

Figure 2: Validity check: Elite-school enrollment and student characteristics



Notes: The figure presents the share of students who enrolled in an elite school by student characteristics. Each cell shows the share of elite-school students for a combination of 5th-grade GPA and the number of books at home. In the top panels (bottom) high-ability/low-ability is defined as having 6th-grade mathematics (reading) test score above/below the median. Sample: 8th-grade sample, N = 126,196.

4.3 School value-added

The non-parametric bound approach offers several advantages (e.g., mild identifying assumptions with testable implications), however, its ability to recover informative estimates may be limited. Therefore, we consider a complementary empirical strategy, which builds on selection on observables—a more demanding assumption.

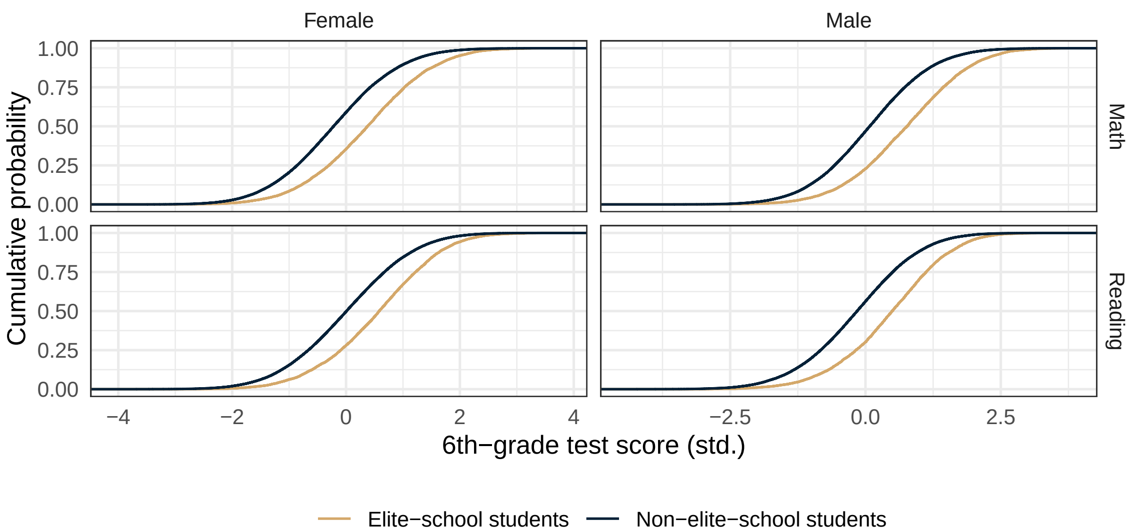
Assumption 3 (Selection on observables)**.**

$$\mathbb{P}\left[Y(d) \geq \gamma | D = d, Z\right] = \alpha_d^\gamma + \beta_d^\gamma Z, \quad d = 0, 1; \forall \gamma,$$

where Z is a vector of variables.

The selection on observables assumption provides point identification for the causal effect

Figure 3: Validity-check: The distribution of students' 6th-grade standardized test scores by elite-school enrollment



Notes: The figure displays the cumulative distribution function of students' 6th-grade standardized test score by elite-school enrollment and gender. The left (right) panels present the distributions for female (male) students. The top (bottom) panels present the distribution of the 6th-grade mathematics (reading) test scores.

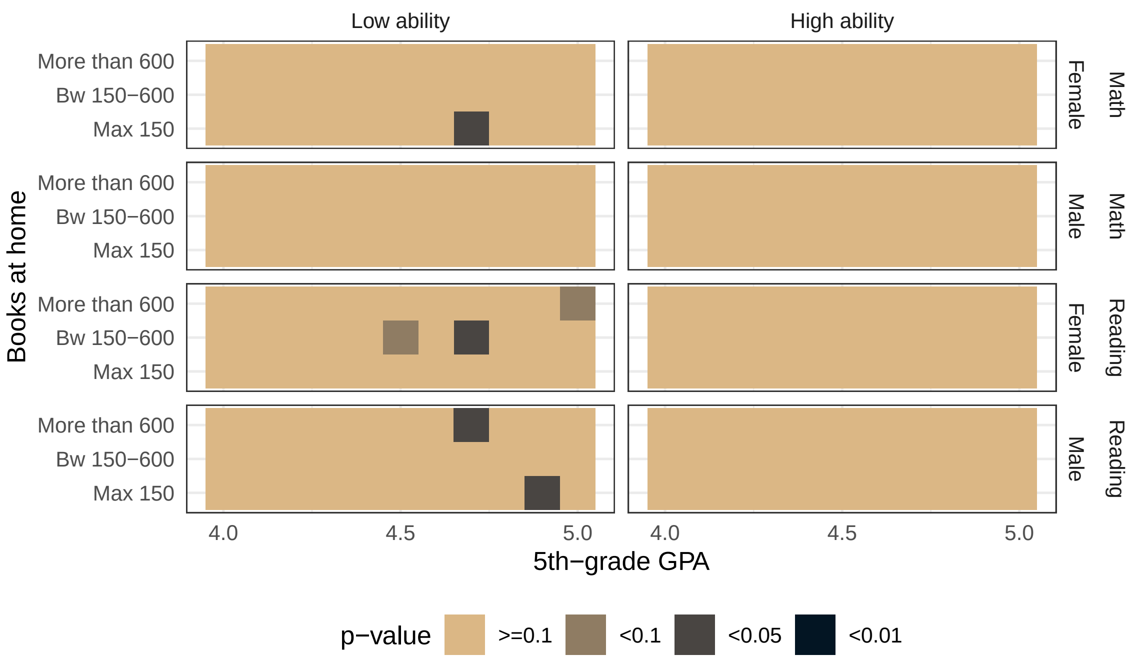
of interest:

$$\tau(\gamma) = \sum_{z \in Z} \left(\alpha_1^{\gamma} - \alpha_0^{\gamma} + (\beta_1^{\gamma} - \beta_0^{\gamma}) z \right) \mathbb{P}\left[D = 1 | Z = z \right].$$

The selection on observables assumption ensures that an ordinary least squares (OLS) regression of Y_i on an indicator of elite-school enrollment interacted with Z_i recovers unbiased estimates of α_d^{γ} and β_d^{γ}. We consider two specifications. First, the vector Z includes students' 6th-grade standardized test scores and cohort fixed effects (*simple* model). Second, the vector Z includes additional covariates, such as 5th-grade GPA, number of books at home, education of the mother, education of the father, being disadvantaged, the county of the school, and the type of the residence where the school is located (*full* model).[13] Both specifications resemble the commonly used "*school value-added*" approach to evaluate the effectiveness of

[13]Appendix C describes the construction of our variables, and Appendix Table A1 presents summary statistics of the additional covariates of the school value-added specifications.

Figure 4: Validity-check: The p-values of the Kolgomorov-Smirnov test



Notes: The figure displays the p-values of the one-sided Kolgomorov-Smirnov test. The Kolgomorov-Smirnov test tests the equality of the distributions of elite-school and non-elite-school students' 6th-grade standardized test scores. Each cell shows the p-value for a combination of 5th-grade GPA and the number of books at home. In the top panels (bottom) high-ability/low-ability is defined as having 6th-grade mathematics (reading) test score above/below the median. Sample: 8th-grade sample, N = 126,196.

schools (Koedel et al., 2015).

The plausibility of the selection on observables assumption is debated in the context of school value-added (school VA) estimates (see e.g., Chetty et al., 2014a,b; Guarino et al., 2015; Rothstein, 2010, 2017). For elite schools in Amsterdam, Oosterbeek et al. (2020) finds that school value-added estimates are severely biased when they are compared to admission lottery-based estimates. In the context of Hungarian elite schools, we view the school value-added estimates complementary to our non-parametric bound approach. We note that when the selection on observables assumption is violated, the direction of the bias of the school value-added estimate is unclear. Therefore, the school value-added estimates might be less informative about our causal effect of interest than the non-parametric bounds.

5 Results

This section presents our results. We begin, in Section 5.1, by showing that enrollment in an elite school has a negative effect on the short-run academic achievement of female and low-ability students. In Section 5.2, we show that our non-parametric bounds strategy cannot rule out moderately positive effects on academic achievement 4 years after enrollment. Finally, in Section 5.3, using value-added models, we show that elite schools improve students' academic achievement 4 years after enrollment.

5.1 Short-run academic achievement

We begin by studying the effect of enrollment in an elite school on elite-school students' 8th-grade mathematics grade. Figure 5 displays the upper bounds on the causal effect of interest, split by ability and gender.[14] The figure also displays the raw (unconditional) differences between the outcomes of elite-school and non-elite school students for each group.

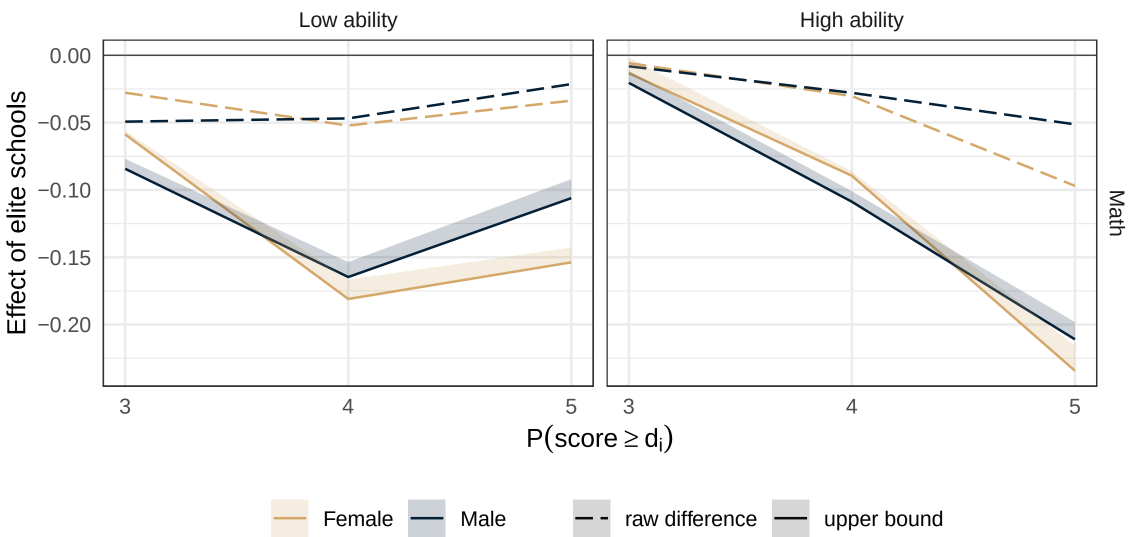
Figure 5 shows that the upper bounds are negative throughout the outcome distribution for each gender–ability group. For example, enrollment in an elite school decreases the probability of having an 8th-grade mathematics grade larger than 4.5 by at least 15 percentage points for high-ability male students. The upper bound of 15 percentage points corresponds to a 21 percent relative decrease (Appendix Figure B1). For high-ability students, the upper bounds are the lowest at the top of the distribution. The upper bounds of the causal effect are considerably lower than the unconditional differences, which is consistent with positive selection into elite schools.

The negative upper-bound estimates on students' 8th-grade mathematics grade do not necessarily reflect negative effects on students' skill formation. Alternative explanations are ceiling effects, grading on a curve (Calsamiglia and Loviglio, 2019), or more demanding study requirements in elite schools. To rule out these alternative explanations, we next examine the effect of elite schools on students' 8th-grade standardized test scores. This test score is

[14] The figure also displays the 95% confidence intervals on the causal effect of interest. Since we present the upper bound estimates of the causal effect exclusively, we mark the area between the upper confidence band and the estimate itself (shaded area).

not top-coded, blindly graded, and standardized nationwide, therefore, it is not susceptible to the above mentioned alternative explanations.

Figure 5: The effect of elite-school enrollment on the distribution of elite-school students' 8th-grade mathematics grade



Notes: The figure presents our upper-bound estimates of the effect of elite-school enrollment on the distribution of elite-school students' 8th-grade mathematics grade (solid lines). The dashed line denotes the raw difference between the outcomes of elite-school and non-elite-school students. We report the estimates separately by gender and low- and high-ability students. Low- and high-ability students are defined by whether the students' 6th-grade mathematics test score is below or above the median. Students' 6th-grade mathematics grade is measured on the scale of 1–5. The shaded area represents the area between the upper confidence band (95%) and the upper bound estimate itself. The 95% confidence intervals are based on 1,000 bootstrap draws. Sample: 8th-grade sample, N = 126,196.

Figure 6 presents the upper bounds on the effect of enrollment in an elite school on the distribution of 8th-grade standardized test scores. The figure displays the upper bounds on the deciles of the distribution of students' mathematics and reading test scores.[15]

The figure shows that enrollment in an elite school has a negative effect on female and low-ability elite-school students' mathematics test scores two years after enrollment. Elite-school enrollment reduces the probability of scoring above the median in mathematics by

[15]To simplify the exposition, Figure 6 displays the bounds only on the bottom- and top-6 deciles of the outcome distribution of low- and high-ability students, respectively.

more than 7.5 percentage points, corresponding to 30 percent, for low-ability female students, and by more than 1 percentage points, corresponding to 10 percent, for low-ability male students. For high-ability female students, we find that elite-school enrollment reduces the probability of scoring in the top 10 percent in mathematics by more than 2 percentage points, corresponding to 10 percent (Appendix Figure B2). The figure also shows that enrollment in an elite school does not meaningfully increase the 8th-grade mathematics test scores of low-ability male students. The upper bounds are actually negative for the fourth and fifth deciles of the outcome distribution. If anything, elite-school enrollment may only raise high-achieving male students' mathematics test score at the top of the outcome distribution, by at most 2–5 percentage points.

The bottom panels of the figure show the effect of enrollment in an elite school on students' 8th-grade reading test scores. We find that the effect is negative for low-ability female students. The bounds do not exclude positive effects for male and high-achieving female students.

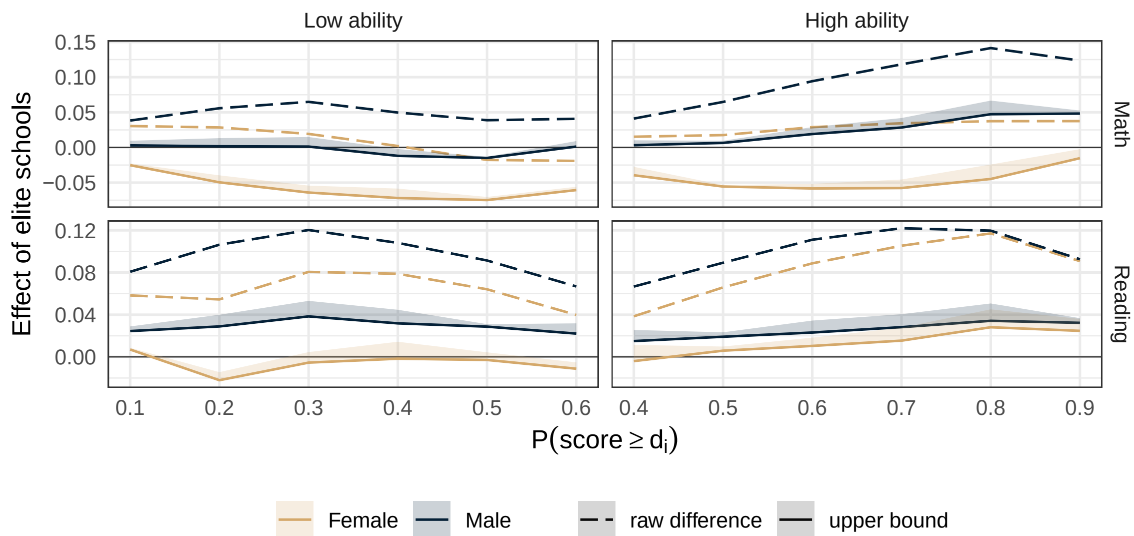
A potential mechanism underlying the negative short-run effects is that elite-school students switch schools, and it may take time for them to adapt to the new environment. We test this hypothesis by conducting a heterogeneity analysis. To this end, we focus on elite-school students who attend a comprehensive school, and thus enrollment in an elite school does not involve switching schools. Figure 7 presents the estimates for this subsample of students. The upper bounds are negative for both male and female students (irrespective of ability) in mathematics. These results suggest that the fact that students in the comparison group do not switch school does not drive our short-run results.[16]

5.2 Medium-run academic achievement

Having found that enrollment in an elite school has a negative effect on female and low-ability students' 8th-grade mathematics test score, we next investigate whether these negative effects persist in grade 10. Figure 8 presents the upper bounds on the effect of enrollment in an elite school on the distribution of 10th-grade test scores. We find that the upper bounds

[16] Appendix Figure A3 shows the estimates for elite-school students who did switch to an elite school. The estimates are largely similar to those presented in Figure 6.

Figure 6: The effect of elite-school enrollment on the distribution of elite-school students' 8th-grade standardized test scores

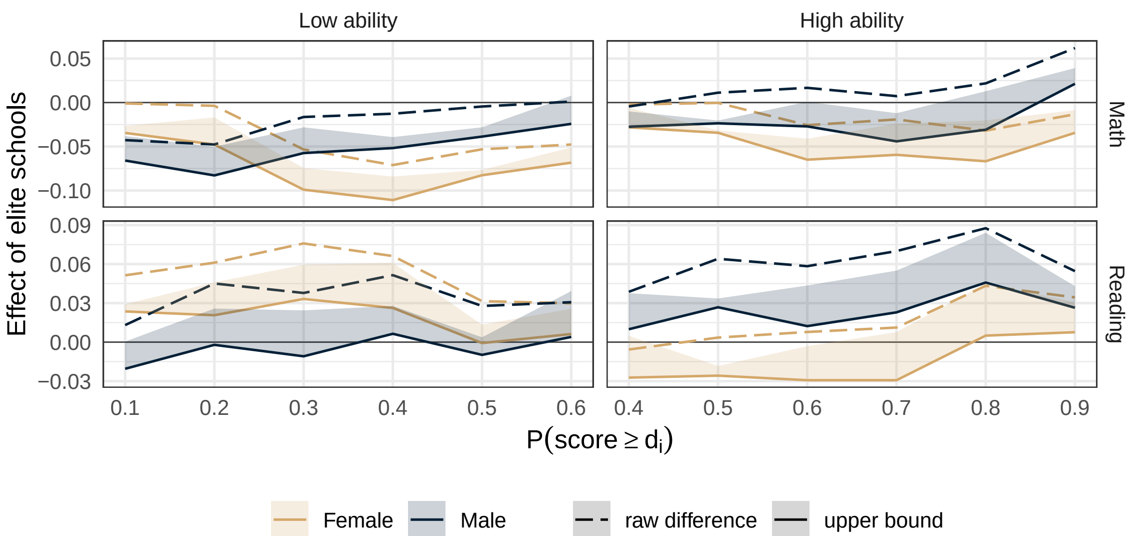


Notes: The figure presents our upper-bound estimates of the effect of elite-school enrollment on the distribution of elite-school students' 8th-grade mathematics grades (solid lines). The dashed line denotes the raw difference between the outcomes of elite-school and non-elite-school students. We report the estimates separately by gender and low- and high-ability students. Low- and high-ability students are defined by whether the students' 6th-grade standardized test score is below or above the median. The shaded area represents the area between the upper confidence band (95%) and the upper bound estimate itself. The 95% confidence intervals are based on 1,000 bootstrap draws. Sample: 8th-grade sample, N = 126,196.

are positive, and relatively large in magnitude, for each subgroup and test (mathematics and reading). These findings are consistent with negative as well as substantial positive effects, and therefore they are inconclusive about the question whether the short-run negative effects persist.

A potential explanation for the high upper bounds is that students who did not enroll in an elite school attend low value-added schools. This concern, for example, is particularly pronounced for vocational schools, whose curriculum has less of an academic orientation. We thus focus on the subset of secondary grammar schools that have elite school tracks and regular tracks as well (see Table 1). Figure 9 presents the upper bounds on this subset of secondary grammar schools. We find that the upper bounds are positive, but considerably lower than the ones presented in Figure 8. For example, the upper bound on the effect of

Figure 7: The effect of elite-school enrollment on the distribution of elite-school students' 8th-grade standardized test scores: Comprehensive schools



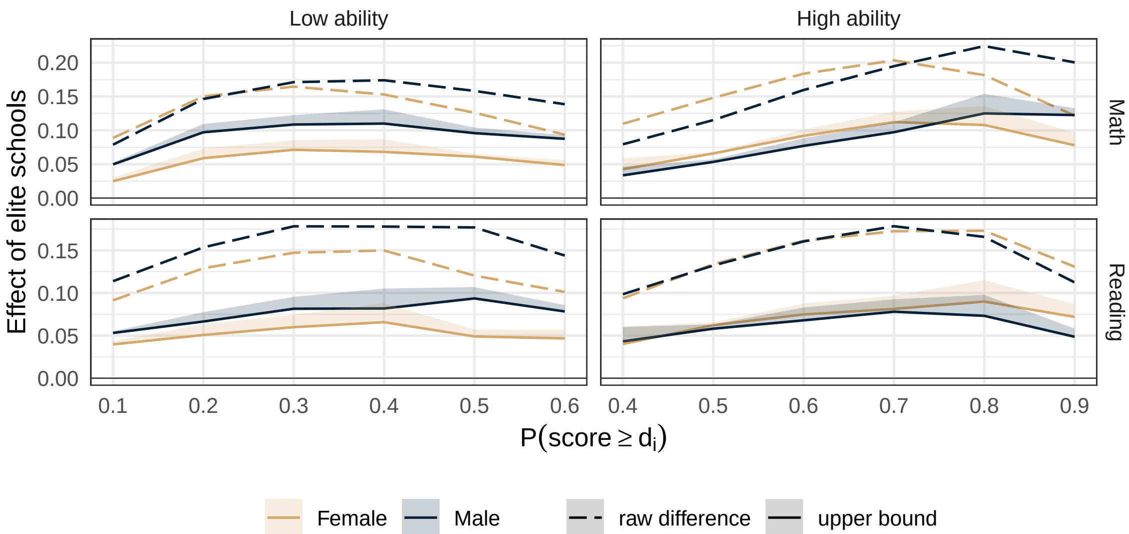
Notes: The figure presents our upper-bound estimates of the effect of elite-school enrollment on the distribution of elite-school students' 8th-grade standardized test scores (solid lines). The dashed line denotes the raw difference between the outcomes of elite-school and non-elite-school students. We report the estimates separately by gender and low- and high-ability students. Low- and high-ability students are defined by whether the students' 6th-grade standardized test score is below or above the median. The shaded area represents the area between the upper confidence band (95%) and the upper bound estimate itself. The 95% confidence intervals are based on 1,000 bootstrap draws. Sample: 8th-grade sample – comprehensive schools, N = 111,501.

having a mathematics test score in the top decile for high-ability male students drops from 12.5 to 6 percentage points. These findings indicate that low value-added secondary-schools (e.g., vocational schools) do not drive the positive upper bounds. Yet, these bounds do not reveal whether the negative effects of elite schools persist.

5.3 School value-added

As our non-parametric bounds strategy is inconclusive about the sign of the effects of elite-school enrollment in the medium run, we turn to the results of our school value-added models. Figure 10 presents the school value-added estimates for students' 8th-grade standardized test scores, in each gender–ability group using two alternative specifications. The simple

Figure 8: The effect of elite-school enrollment on the distribution of elite-school students' 10th-grade standardized test scores

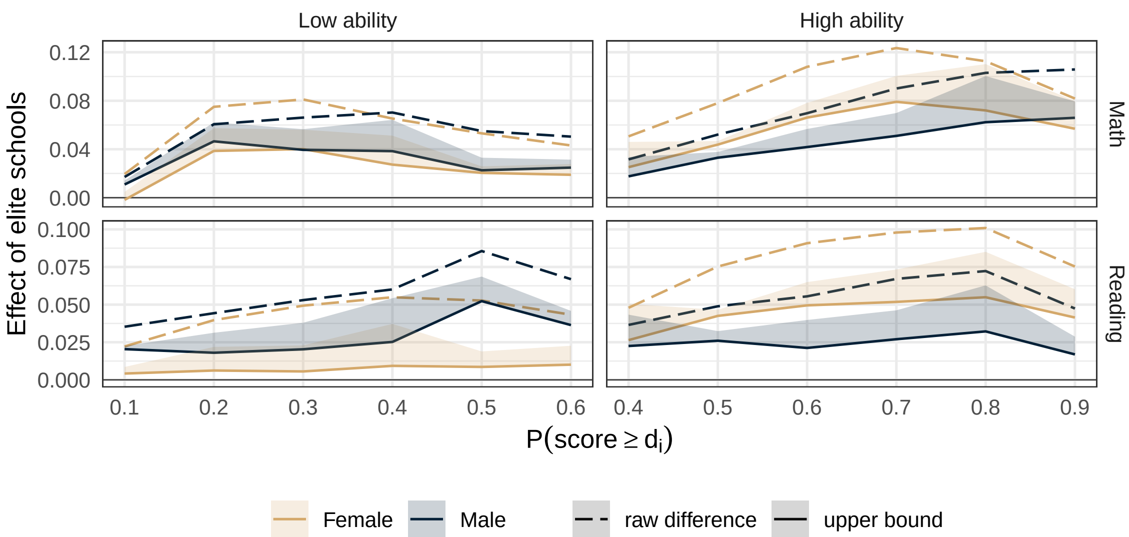


Notes: The figure presents our upper-bound estimates of the effect of elite-school enrollment on the distribution of elite-school students' 10th-grade standardized test scores (solid lines). The dashed line denotes the raw difference between the outcomes of elite-school and non-elite-school students. We report the estimates separately by gender and low- and high-ability students. Low- and high-ability students are defined by whether the students' 6th-grade standardized test score is below or above the median. The shaded area represents the area between the upper confidence band (95%) and the upper bound estimate itself. The 95% confidence intervals are based on 1,000 bootstrap draws. Sample: 10th-grade sample, N = 71,962.

model controls for students' 6th-grade standardized test score and cohort fixed effects. The full model adds additional controls for student and school characteristics (see Section 4.3).

The figure corroborates that enrollment in an elite school has a negative effect on female elite-school students' 8th-grade mathematics test scores throughout the outcome distribution. The simple model shows that enrollment in an elite school decreases the probability of having a mathematics test score above the median by 5 percentage points for low-ability, and 3 percentage points for high-ability female students. The full model with additional covariates suggests that the effect is about minus 7.5 percentage points for low-ability, and minus 8 percentage points for high-ability female students. The negative relative effect of elite-school enrollment is larger for low-ability female students and at the top of the outcome distribution (Appendix Figure B6).

Figure 9: The effect of elite-school enrollment on the distribution of elite-school students' 10th-grade standardized test scores: Elite-school subsample

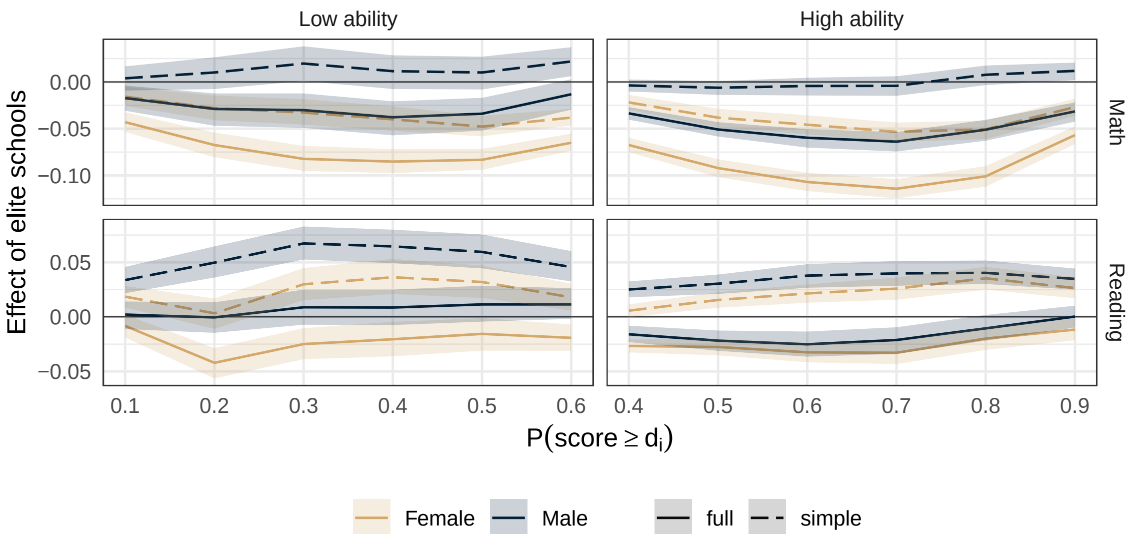


Notes: The figure presents our upper-bound estimates of the effect of elite-school enrollment on the distribution of elite-school students' 10th-grade standardized test scores (solid lines). The dashed line denotes the raw difference between the outcomes of elite-school and non-elite-school students. We report the estimates separately by gender and low- and high-ability students. Low- and high-ability students are defined by whether the students' 6th-grade standardized test score is below or above the median. The shaded area represents the area between the upper confidence band (95%) and the upper bound estimate itself. The 95% confidence intervals are based on 1,000 bootstrap draws. Sample: 10th-grade sample – elite-school subsample, N = 21,384.

Figure 10 also reiterates that elite-school enrollment does not meaningfully increase the 8th-grade mathematics test scores of low-ability male students. The estimates of the simple school VA model are close to zero for both low- and high ability male students throughout the entire outcome distribution. The full model with additional covariates indicates that the effect is negative. Similar to female students, we find that the size of the relative effects are larger for low-ability male students relative to high-ability male students, and at the top of the outcome distribution (Appendix Figure B6).

The school value-added estimates are less robust when we study the effect of elite-school enrollment on elite-school students' 8th-grade reading scores. The simple model yields positive estimates for each ability-gender group throughout the outcome distribution. By contrast, the full model results in negative or insignificant estimates. We find that the full model's results are consistent with our non-parametric bounds (Appendix Figure A4).

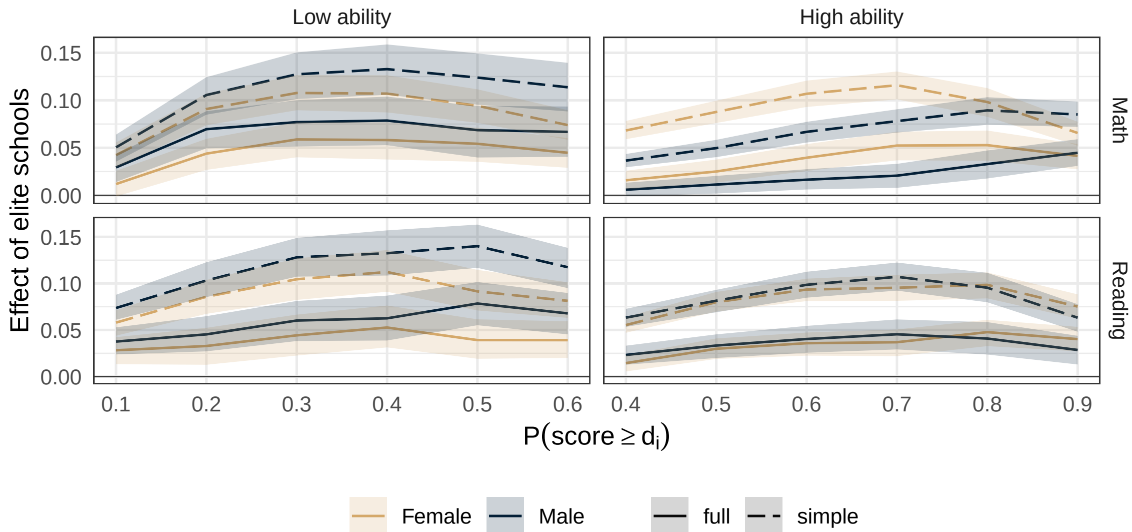
Figure 10: The effect of elite-school enrollment on the distribution of elite-school students' 8th-grade test scores: School VA



Notes: The figure presents the school value-added estimates of the effect of elite-school enrollment on the distribution of elite-school students' 8th-grade standardized test scores. The figure presents school VA estimates for the deciles of the outcome distribution. The top (bottom) panels focus on mathematics (reading). The left (right) panels focus on students whose 6th-grade test score is above (below) the median. The dashed lines refer to the estimates of the simple school VA model (6th-grade standardized test score, cohort fixed effects) and the solid lines refer to the full school VA model (6th-grade standardized test score, cohort fixed effects, 5th-grade GPA, number of books at home, parental education, disadvantaged status, county of the school, type of the settlement where the school is located). The shaded are represents the 95% confidence intervals around the school VA estimates. The confidence intervals are based on 1,000 bootstrap draws. Sample: 8th-grade sample, N = 126,196.

Figure 11 presents the school VA estimates for elite-school students' 10th-grade standardized test scores. We find that elite-school enrollment has a positive effect on elite-school students' 10th-grade test scores for both ability groups. The full model suggests that elite-school enrollment increases the probability of having a mathematics test score above the median by 10 percentage points for low-ability female students, and 12.5 percentage points for low-ability male students. For high-ability students, we find that the effect on the probability of having a mathematics test score above the 9th decile is 7 percentage points for girls, and 8 percentage points for boys. The relative effect of elite-school enrollment on the mathematics test score is heterogeneous for high-ability students. We find that the relative effect for high-ability female students is higher than those of high-ability male students. By contrast, the relative effects do not differ between low-ability female and male students. We also find that the relative effect is higher at the top of the outcome distribution (Appendix Table B7).

Figure 11: The effect of enrollment in an elite school on the distribution of elite-school students' 10th-grade test scores: School VA



Notes: The figure presents the school value-added estimates of the effect of elite-school enrollment on the distribution of elite-school students' 10th-grade standardized test scores. The figure presents school VA estimates for the deciles of the outcome distribution. The top (bottom) panels focus on mathematics (reading). The left (right) panels focus on students whose 6th-grade test score is below (above) the median. The dashed lines refer to the estimates of the simple school VA model (6th-grade standardized test score, cohort fixed effects) and the solid lines refer to the full school VA model (6th-grade standardized test score, cohort fixed effects, 5th-grade GPA, number of books at home, parental education, disadvantaged status, county of the school, type of the settlement where the school is located). The shaded are represents the 95% confidence intervals around the school VA estimates. The confidence intervals are based on 1,000 bootstrap draws. Sample: 10th-grade sample, N = 71,962.

6 Conclusions

We have studied the effect on enrollment in an elite school on elite-school students' short- and medium-run academic achievement. Motivated by the fact that local effects identified at the margin of admission may not generalize to the average elite-school student, the causal effect of interest has been the average treatment effect on the treated. To identify the causal effects of interest, we have used non-parametric bounds and school value-added models. To further understand the heterogeneous effects of elite schools, we have conducted our analysis by gender-ability groups, and we have studied the effects throughout the outcome distribution.

Our main finding is that enrollment in an elite school has a negative effect on female and low-ability students' mathematics test scores on the short run. By contrast, our non-parametric bounds strategy does not allow us to exclude small, positive effects for high-ability male students. We argue that the short-run negative effects are not the consequence of grading policies (e.g., grading on a curve, ceiling effects), but they reflect real effects in skill formation. As non-parametric bounds are uninformative about the sign of the medium-run effects, we have used school value-added models to test whether the negative short-run effects persist. These school value-added estimates suggest that elite-school enrollment has a positive effect on academic achievement for each gender-ability group on the medium run.

The most salient difference between an average elite-school student and a student on the margin of admission is her (baseline) academic ability. Therefore, our analysis has focused on effect heterogeneity along the ability distribution. Splitting the sample by baseline ability suggests that high-ability students benefit more from elite-school enrollment. By studying the effect of elite-school enrollment throughout the outcome distribution, our findings indicate that the benefits of elite schools are concentrated at the top of the test score distribution.

Our study design does not allow us to identify the exact mechanisms driving our results. Nonetheless, heterogeneity analysis along school characteristics enables us to exclude some important mechanisms. First, the negative upper bounds on the short-run effects in comprehensive schools suggest that school switching does not explain the negative short-run effects of elite schools. Second, the positive upper bounds on medium-run outcomes are not solely driven by less selective schools in the counterfactual.

We have focused on how elite-school enrollment affect academic achievement. However, parents may also value schools along other dimensions, such as non-cognitive skills, field of study, college enrollment, or labor market outcomes (see, e.g., Beuermann and Jackson, Forthcoming; Beuermann et al., 2018).[17] We view the understanding of how elite schools affect these outcomes as fruitful directions for future research.

[17]The strong positive association between Hungarian students' standardized test scores and their labor market outcomes (such as employment and wages) suggests that the medium-run benefits in academic achievement may turn into long-run gains in the labor market (Hermann et al., 2019).

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A Additional Tables

Section A.1 presents additional summary statistics on the variables we use in our school value-added models. Section A.2 presents validity checks for the 10th-grade sample. Section A.3 presents additional results and compares the non-parametric bounds to the school value-added estimates.

A.1 Data

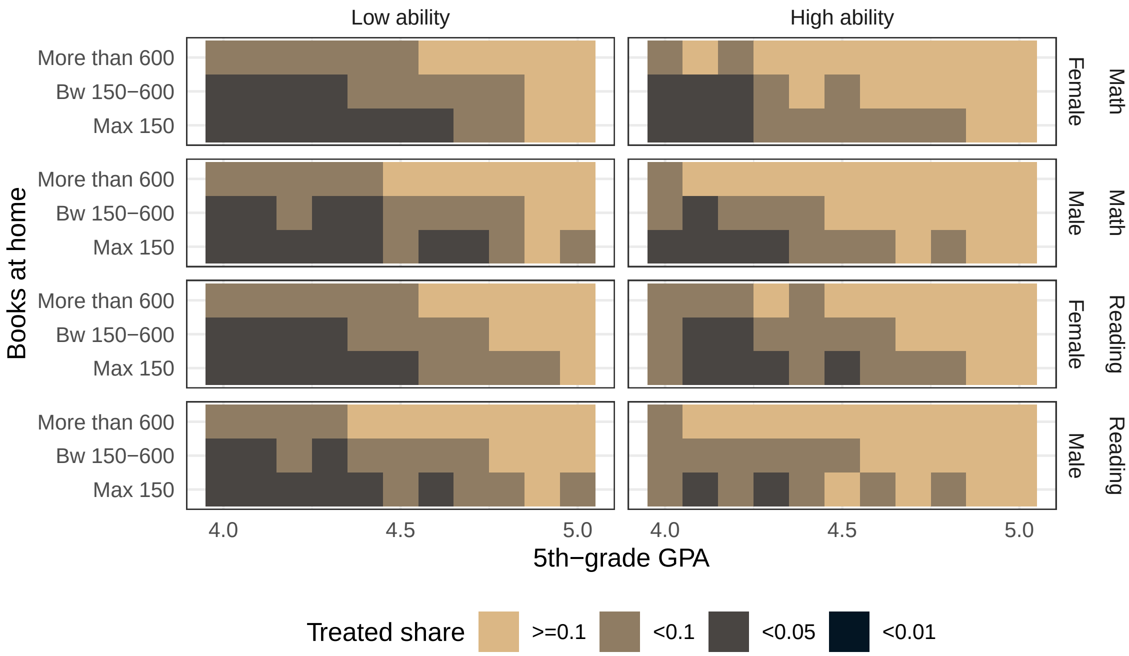
Table A1: Additional summary statistics

	8th-grade sample			10th-grade sample		
	Elite-school students (1)	Non-elite-school students (2)	Total (3)	Elite-school students (4)	Non-elite-school students (5)	Total (6)
A. *Pre-treatment student characteristics*						
Primary education (father)	0.02	0.06	0.05	0.01	0.05	0.04
	(0.12)	(0.23)	(0.22)	(0.11)	(0.21)	(0.20)
Secondary education (father)	0.48	0.69	0.67	0.48	0.69	0.66
	(0.50)	(0.46)	(0.47)	(0.50)	(0.46)	(0.47)
Tertiary education (father)	0.50	0.25	0.28	0.51	0.26	0.29
	(0.50)	(0.43)	(0.45)	(0.50)	(0.44)	(0.46)
Primary education (mother)	0.02	0.07	0.06	0.02	0.06	0.05
	(0.12)	(0.25)	(0.23)	(0.13)	(0.23)	(0.22)
Secondary education (mother)	0.40	0.62	0.59	0.39	0.61	0.58
	(0.49)	(0.49)	(0.49)	(0.49)	(0.49)	(0.49)
Tertiary education (mother)	0.58	0.32	0.35	0.59	0.34	0.37
	(0.49)	(0.47)	(0.48)	(0.49)	(0.47)	(0.48)
Disadvantaged	0.00	0.03	0.03	0.00	0.01	0.01
	(0.07)	(0.17)	(0.16)	(0.06)	(0.12)	(0.12)
B. *School location*						
Capital or county capital	0.59	0.41	0.44	0.59	0.64	0.63
	(0.49)	(0.49)	(0.50)	(0.49)	(0.48)	(0.48)
Town	0.41	0.40	0.40	0.41	0.36	0.36
	(0.49)	(0.49)	(0.49)	(0.49)	(0.48)	(0.48)
Village	0.00	0.19	0.16	0.00	0.00	0.00
	(0.00)	(0.39)	(0.37)	(0.00)	(0.07)	(0.06)
Number of students	16,702	109,494	126,196	8,850	63,112	71,962

Notes: The table presents the means and standard deviations of student characteristics for each sample. Columns (1) and (4) focus on students who did not enroll in an elite school, columns (2) and (5) focus on students who enrolled in an elite school, and columns (3) and (6) focus on the entire sample.

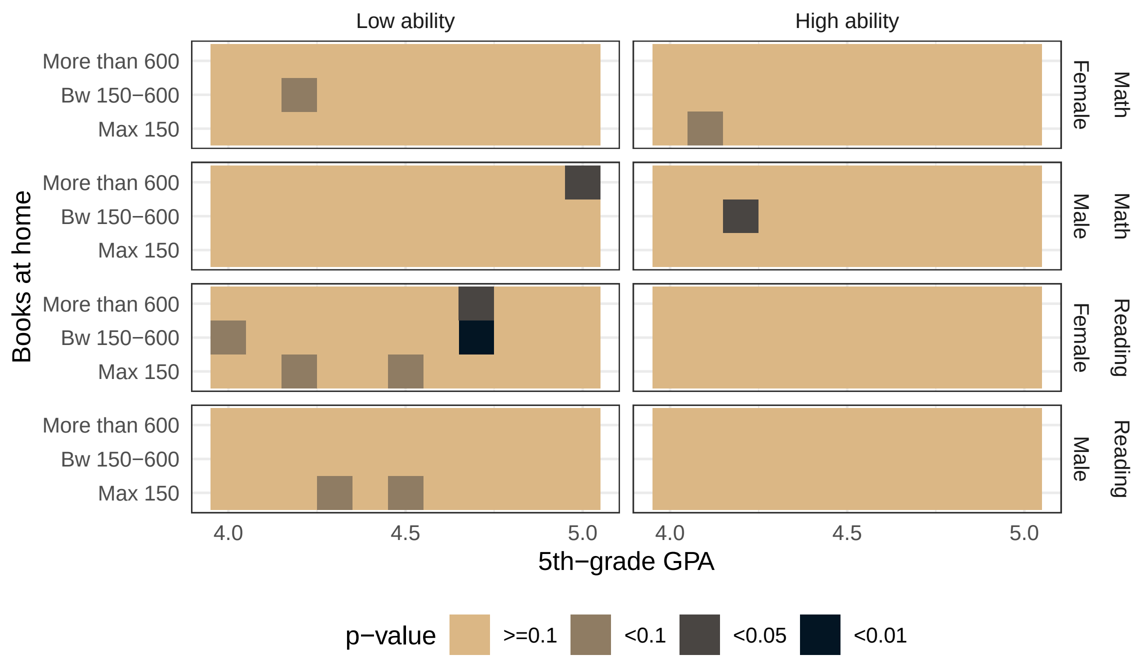
A.2 Validity check

Figure A1: Validity check: Elite-school enrollment and student characteristics – 10th-grade sample



Notes: The figure presents the share of students who enrolled in an elite school by student characteristics. Each cell shows the share of elite-school students for a combination of 5th-grade GPA and the number of books at home. In the top panels (bottom) high-ability/low-ability is defined as having 6th-grade mathematics (reading) test score above/below the median. Sample: 10th-grade sample, N = 71,962.

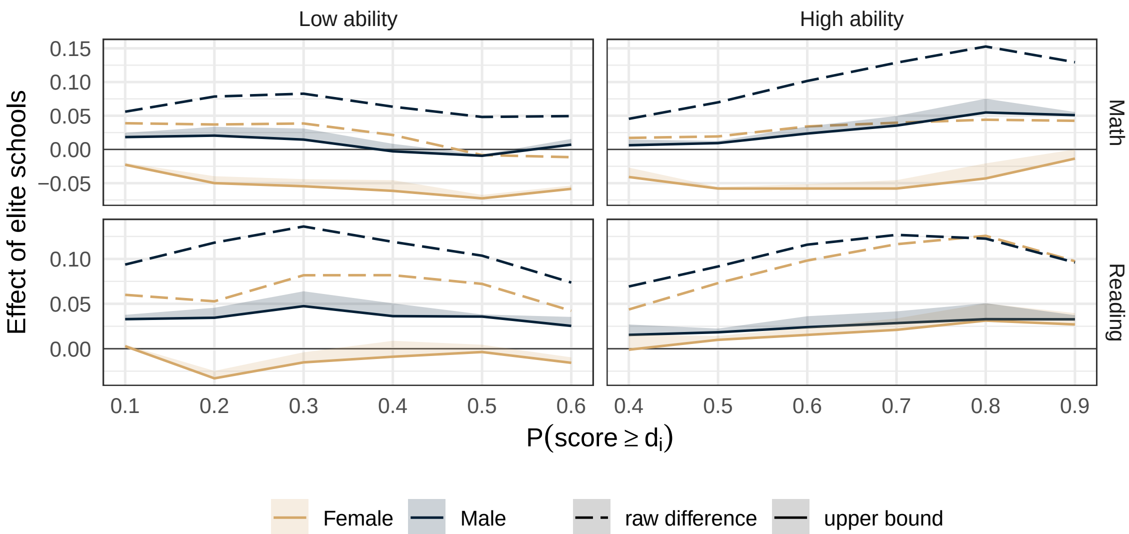
Figure A2: Validity check: The p-values of the Kolgomorov-Smirnov test – 10th-grade sample



Notes: The figure displays the p-values of the one-sided Kolgomorov-Smirnov test. The Kolgomorov-Smirnov test tests the equality of the distributions of elite-school and non-elite-school students' 6th-grade standardized test scores. Each cell shows the p-value for a combination of 5th-grade GPA and the number of books at home. In the top panels (bottom) high-ability/low-ability is defined as having 6th-grade mathematics (reading) test score above/below the median. Sample: 10th-grade sample, N = 71,962.

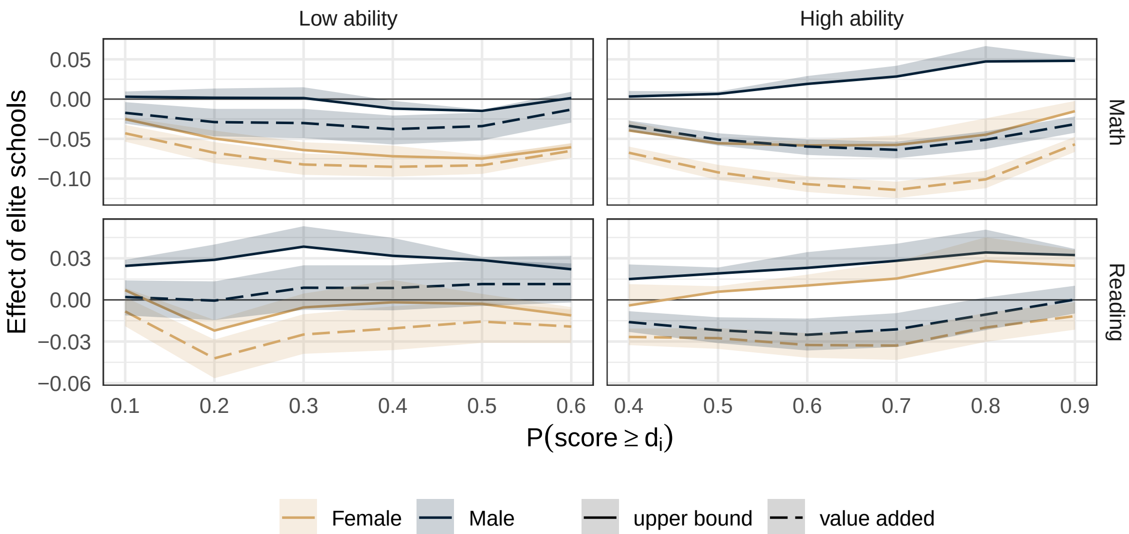
A.3 Results

Figure A3: The effect of elite-school enrollment on the distribution of elite-school students' 8th-grade standardized test scores: Non-comprehensive schools



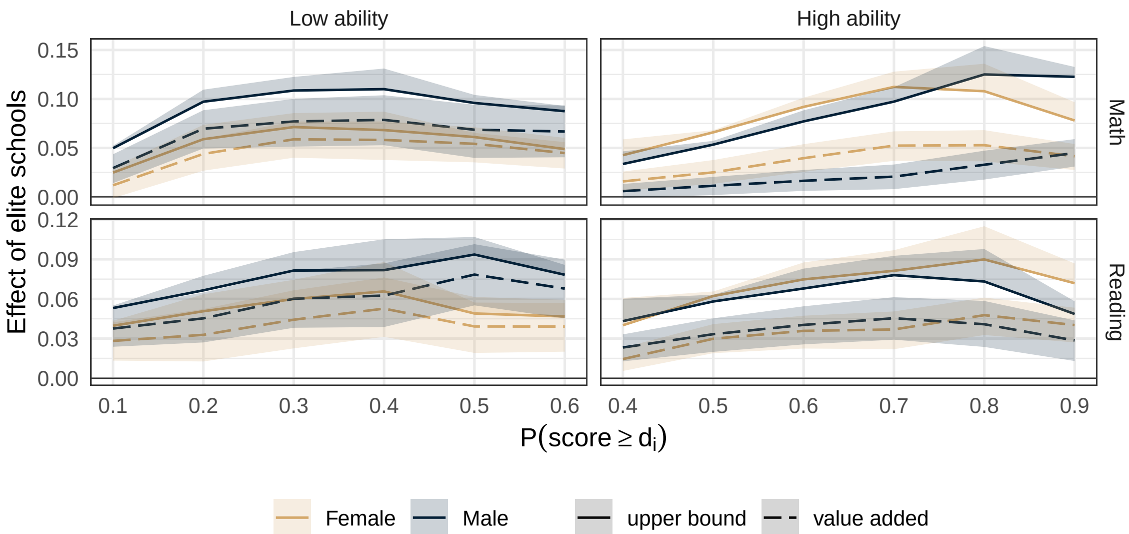
Notes: The figure presents our upper-bound estimates of the effect of elite-school enrollment on the distribution of elite-school students' 8th-grade standardized test scores (solid lines). The dashed line denotes the raw difference between the outcomes of elite-school and non-elite-school students. We report the estimates separately by gender and low- and high-ability students. Low- and high-ability students are defined by whether the students' 6th-grade standardized test score is below or above the median. The shaded area represents the area between the upper confidence band (95%) and the upper bound estimate itself. The 95% confidence intervals are based on 1,000 bootstrap draws. Sample: 8th-grade sample – non-comprehensive schools, N = 124,189.

Figure A4: The effect of elite-school enrollment on the distribution of elite-school students' 8th-grade standardized test scores: Bounds and school VA



Notes: The figure presents our upper-bound estimates of the effect of elite-school enrollment on the distribution of elite-school students' 8th-grade standardized test scores (solid lines) along with the school value-added estimates of full model (dashed lines). The figure presents the estimates for the deciles of the outcome distribution. We report the estimates separately by gender and ability. Low- and high-ability students are defined by whether the students' 6th-grade standardized test score is below or above the median. The shaded area represents the 95% confidence intervals (for the bound estimate, only the upper confidence bound is plotted) based on 1,000 bootstrap draws. Sample: 8th-grade sample, N = 126,196.

Figure A5: The effect of elite-school enrollment on the distribution of elite-school students' 10th-grade standardized test scores: Bounds and school VA



Notes: The figure presents our upper-bound estimates of the effect of elite-school enrollment on the distribution of elite-school students' 10th-grade standardized test scores (solid lines) along with the school value-added estimates of full model (dashed lines). The figure presents the estimates for the deciles of the outcome distribution. We report the estimates separately by gender and ability. Low- and high-ability students are defined by whether the students' 6th-grade standardized test score is below or above the median. The shaded area represents the 95% confidence intervals (for the bound estimate, only the upper confidence bound is plotted) based on 1,000 bootstrap draws. Sample: 10th-grade sample, N = 71,962.

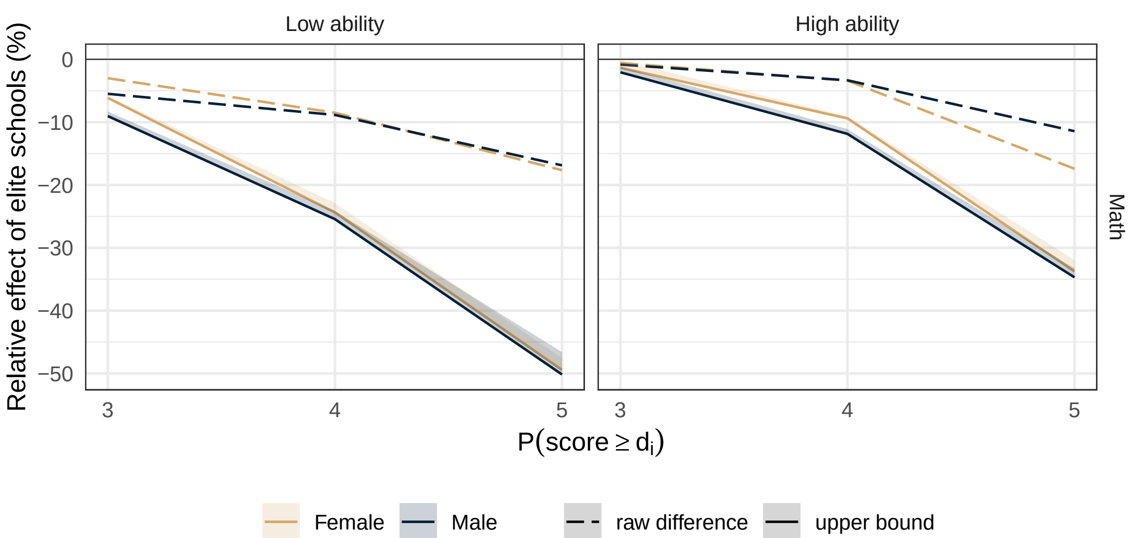
B The relative effects of elite-school enrollment

This Appendix presents non-parametric bounds on the *relative ATET*, i.e., the relative effect of enrollment in an elite school for elite-school students. We define the relative ATET as follows:

$$\text{Relative ATET} = \frac{\mathbb{P}\left[Y(1) > \gamma | D = 1\right]}{\mathbb{P}\left[Y(0) > \gamma | D = 1\right]} - 1 = \frac{\tau(\gamma)}{\mathbb{P}\left[Y(1) > \gamma | D = 1\right] - \tau(\gamma)}, \quad \forall \gamma.$$

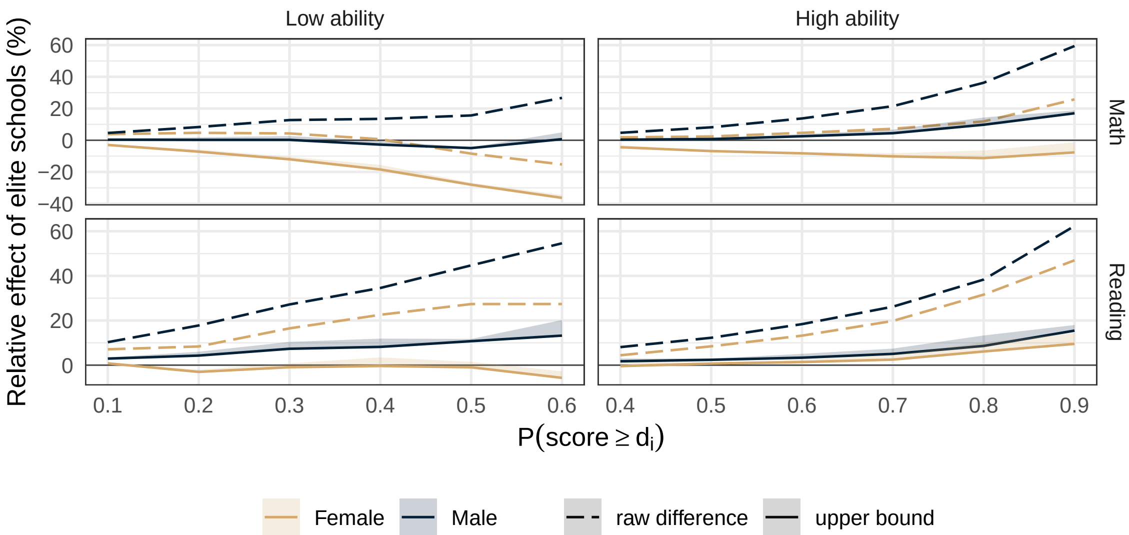
In this Appendix, we present the relative ATET estimates for each figure presented in the main text.

Figure B1: The relative effect of elite-school enrollment on the distribution of elite-school students' 8th-grade mathematics grade



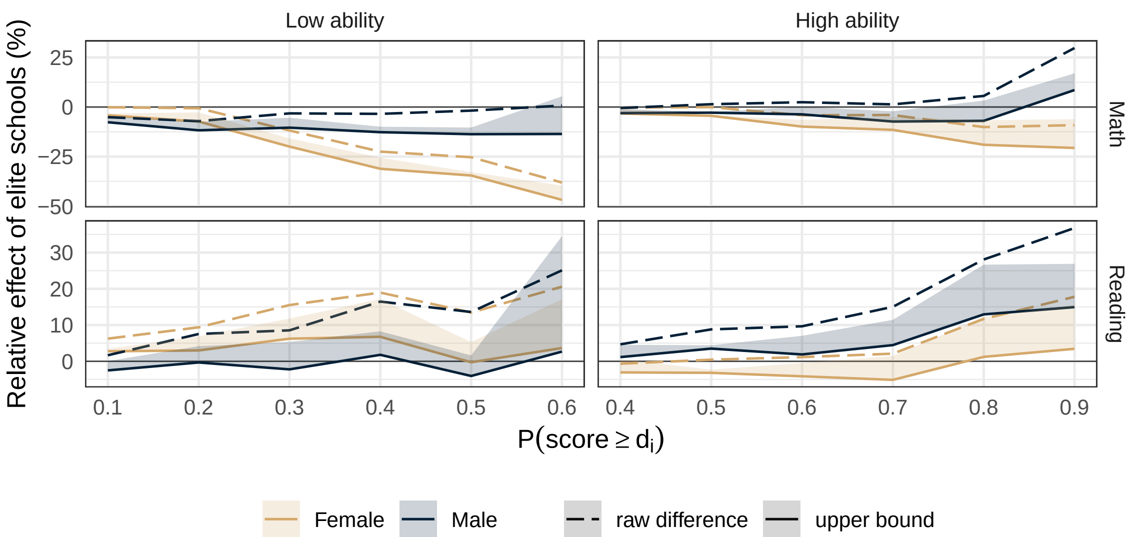
Notes: The figure presents our upper-bound estimates of the **relative** effect of elite-school enrollment on the distribution of elite-school students' 8th-grade mathematics grade (solid lines). The dashed line denotes the raw difference between the outcomes of elite-school and non-elite-school students. We report the estimates separately by gender and low- and high-ability students. Low- and high-ability students are defined by whether the students' 6th-grade mathematics test score is below or above the median. Students' 6th-grade mathematics grade is measured on the scale of 1–5. The shaded area represents the area between the upper confidence band (95%) and the upper bound estimate itself. The 95% confidence intervals are based on 1,000 bootstrap draws. Sample: 8th-grade sample, N = 126,196.

Figure B2: The relative effect of elite-school enrollment on the distribution of elite-school students' 8th-grade standardized test scores



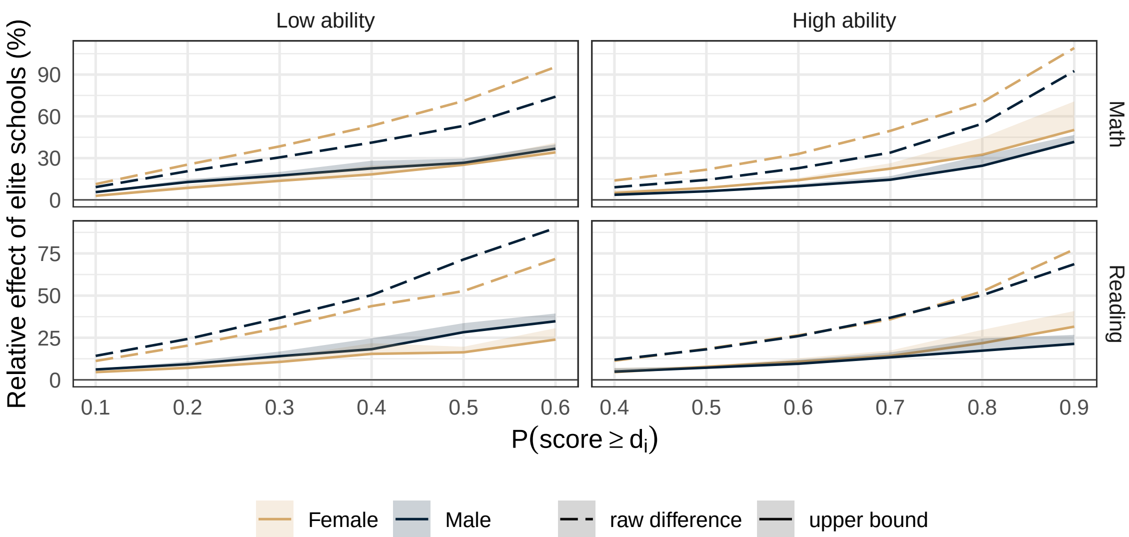
Notes: The figure presents our upper-bound estimates of the **relative** effect of elite-school enrollment on the distribution of elite-school students' 8th-grade mathematics grades (solid lines). The dashed line denotes the raw difference between the outcomes of elite-school and non-elite-school students. We report the estimates separately by gender and low- and high-ability students. Low- and high-ability students are defined by whether the students' 6th-grade standardized test score is below or above the median. The shaded area represents the area between the upper confidence band (95%) and the upper bound estimate itself. The 95% confidence intervals are based on 1,000 bootstrap draws. Sample: 8th-grade sample, N = 126,196.

Figure B3: The relative effect of elite-school enrollment on the distribution of elite-school students' 8th-grade standardized test scores: Comprehensive schools



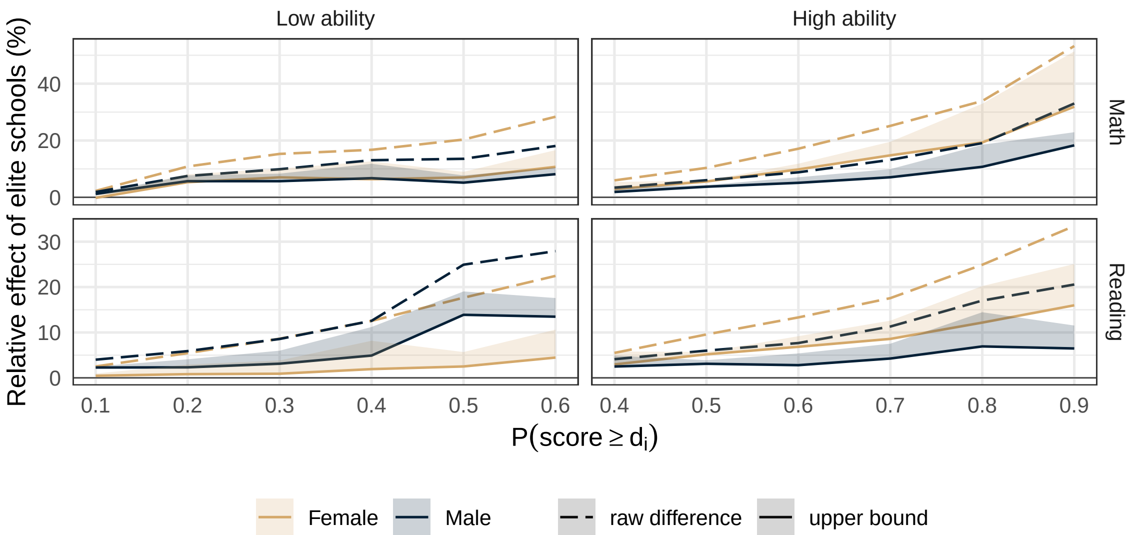
Notes: The figure presents our upper-bound estimates of the **relative** effect of elite-school enrollment on the distribution of elite-school students' 8th-grade mathematics grades (solid lines). The dashed line denotes the raw difference between the outcomes of elite-school and non-elite-school students. We report the estimates separately by gender and low- and high-ability students. Low- and high-ability students are defined by whether the students' 6th-grade standardized test score is below or above the median. The shaded area represents the area between the upper confidence band (95%) and the upper bound estimate itself. The 95% confidence intervals are based on 1,000 bootstrap draws. Sample: 8th-grade sample – comprehensive schools, N = 111,501.

Figure B4: The relative effect of elite-school enrollment on the distribution of elite-school students' 10th-grade standardized test scores



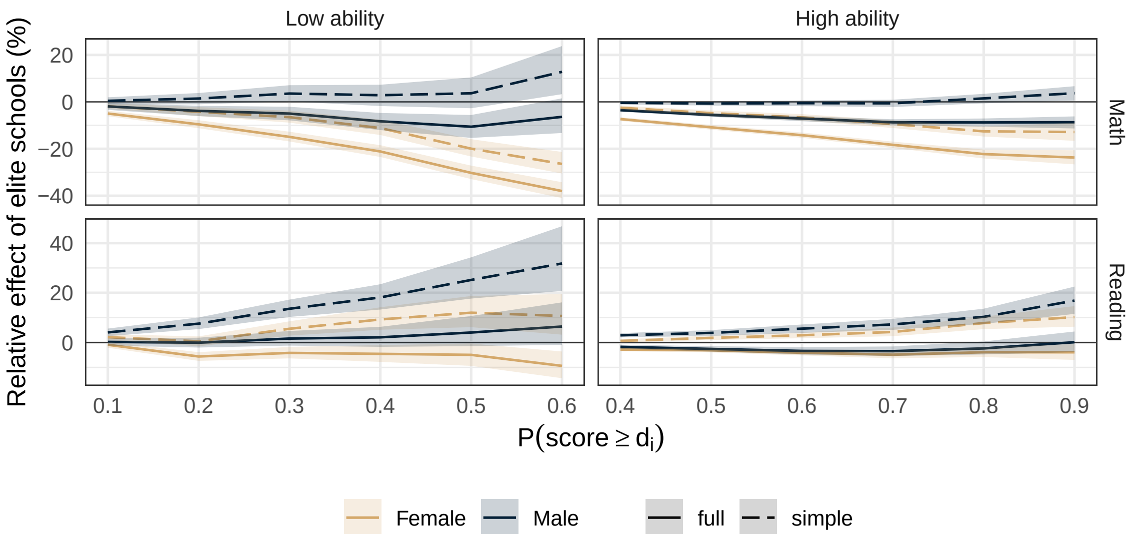
Notes: The figure presents our upper-bound estimates of the **relative** effect of elite-school enrollment on the distribution of elite-school students' 10th-grade standardized test scores (solid lines). The dashed line denotes the raw difference between the outcomes of elite-school and non-elite-school students. We report the estimates separately by gender and low- and high-ability students. Low- and high-ability students are defined by whether the students' 6th-grade standardized test score is below or above the median. The shaded area represents the area between the upper confidence band (95%) and the upper bound estimate itself. The 95% confidence intervals are based on 1,000 bootstrap draws. Sample: 10th-grade sample, N = 71,962.

Figure B5: The relative effect of elite-school enrollment on the distribution of elite-school students' 10th-grade standardized test scores: Elite secondary grammar schools



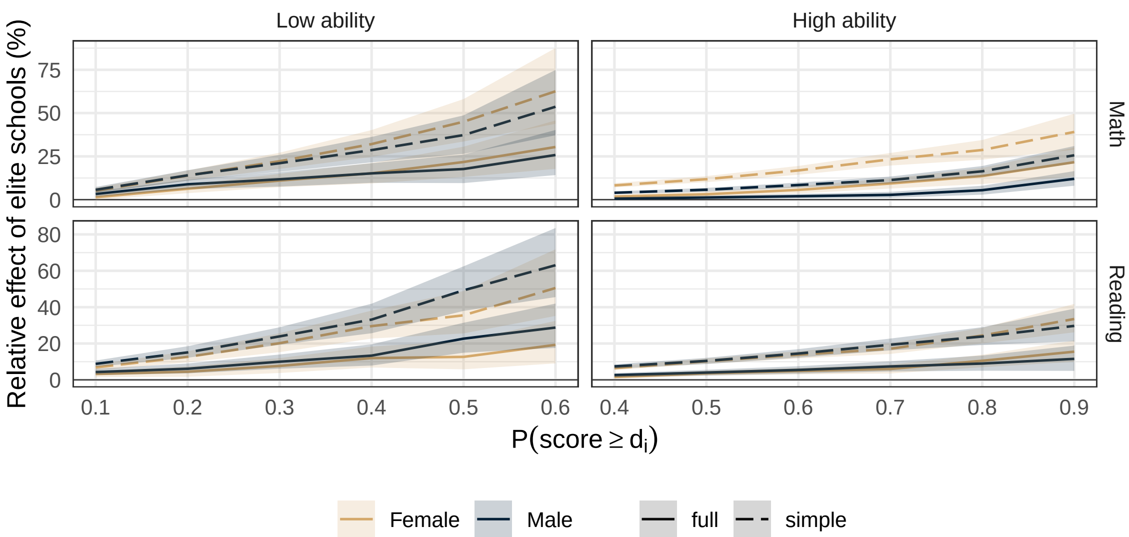
Notes: The figure presents our upper-bound estimates of the effect of elite-school enrollment on the distribution of elite-school students' 10th-grade standardized test scores (solid lines). The dashed line denotes the raw difference between the outcomes of elite-school and non-elite-school students. We report the estimates separately by gender and low- and high-ability students. Low- and high-ability students are defined by whether the students' 6th-grade standardized test score is below or above the median. The shaded area represents the area between the upper confidence band (95%) and the upper bound estimate itself. The 95% confidence intervals are based on 1,000 bootstrap draws. Sample: 10th-grade sample – elite secondary grammar schools, N = 21,384.

Figure B6: The relative effect of elite-school enrollment on the distribution of elite-school students' 8th-grade standardized test scores: School VA



Notes: The figure presents the school value-added estimates of the **relative** effect of elite-school enrollment on the distribution of elite-school students' 8th-grade standardized test scores. The figure presents school VA estimates for the deciles of the outcome distribution. The top (bottom) panels focus on mathematics (reading). The left (right) panels focus on students whose 6th-grade test score is above (below) the median. The dashed lines refer to the estimates of the simple school VA model (6th-grade standardized test score, cohort fixed effects) and the solid lines refer to the full school VA model (6th-grade standardized test score, cohort fixed effects, 5th-grade GPA, number of books at home, parental education, disadvantaged status, county of the school, type of the settlement where the school is located). The shaded are represents the 95% confidence intervals around the school VA estimates. The confidence intervals are based on 1,000 bootstrap draws. Sample: 8th-grade sample, N = 126,196.

Figure B7: The relative effect of elite-school enrollment on the distribution of elite-school students' 10th-grade standardized test scores: School VA



Notes: The figure presents the school value-added estimates of the **relative** effect of elite-school enrollment on the distribution of elite-school students' 8th-grade standardized test scores. The figure presents school VA estimates for the deciles of the outcome distribution. The top (bottom) panels focus on mathematics (reading). The left (right) panels focus on students whose 6th-grade test score is above (below) the median. The dashed lines refer to the estimates of the simple school VA model (6th-grade standardized test score, cohort fixed effects) and the solid lines refer to the full school VA model (6th-grade standardized test score, cohort fixed effects, 5th-grade GPA, number of books at home, parental education, disadvantaged status, county of the school, type of the settlement where the school is located). The shaded are represents the 95% confidence intervals around the school VA estimates. The confidence intervals are based on 1,000 bootstrap draws. Sample: 10th-grade sample, N = 71,962.

C Data (for online publication)

This Appendix describes our data. We begin, in Section C.1, by describing our sample restrictions. In Section C.2, we explain how we construct our variables. Finally, in Section C.3, we describe our approach to imputation.

C.1 Sample restrictions

Table C1 presents the evolution of the sample size as a result of our sample restrictions.

Table C1: Evolution of the sample size

	2010	2011	2012	2013	2014	Total
A. *8th-grade sample*						
raw	104,266	96,843	92,966	89,913	87,542	471,530
w/o missing test score	96,212	89,005	85,245	81,919	80,065	432,446
w/o missing variables	76,875	70,777	68,278	66,636	65,651	348,217
w/o missing after imputation	91,372	84,562	81,441	75,971	74,637	407,983
w/o missing history	62,637	57,651	56,943	53,660	53,703	284,594
final sample	27,328	25,550	25,326	24,275	23,717	126,196
B. *10th-grade sample*						
raw			102,037	95,649	90,188	287,874
w/o missing test score			90,315	83,554	78,727	252,596
w/o missing variables			72,697	68,041	64,963	205,701
w/o missing after imputation			84,911	78,561	74,433	237,905
w/o missing history			54,062	48,945	47,365	150,372
final sample			25,371	23,519	23,072	71,962

Notes: The first row shows the number of students in our raw data, the National Assessment of Basic Competencies (NABC), in each of the relevant years and grades. We document how much of them we lose due to missing test scores and missing background variables. We win back a part of this loss by imputing background variables (see Appendix C.3 for more detail), resulting in a sample of more than 80% of the whole cohorts. Unfortunately, we can only link 60-70% of these students to their 6th-grade results. Restricting the sample to those for whom elite school seems to be a relevant option (having good grades and being in a school in 6th grade from which at least one student goes into an elite school in our sample period) further decreases the size: we end up with about 25% of the cohorts. Our samples are highly selective, but that makes them more relevant for our question.

C.2 Variable description

This Appendix describes the construction of variables in Tables 2 and A1.

- **Number of books at home** is categorical variable with three values: max. 150 books, between 150 and 600 books, and more than 600 books;
- **Mother's education** is a categorical variable with three values: primary, secondary, and tertiary education;
- **Father's education** is a categorical variable with three values: primary, secondary, and tertiary education;
- **Disadvantaged status** is a binary variable, which takes a value of one when a student has a disadvantaged status (i.e., comes from a low-income family);
- **The type of the settlement** where the school is located is a categorical variable with four values: village, town, county capital, capital;
- **County** of the school is a categorical variable with 20 values;

C.3 Imputation

Student's characteristics (number of books at home, mother's education, father's education, disadvantaged status) are gained from an extensive background survey that complements the NABC and which the students fill out together with their parents on a voluntary basis (the average completing rate is around 75 percent, see Table C1). As these characteristics should be mainly constant over time, we could exploit the longitudinal aspect of our data to fill out missing values in one year from the corresponding questionnaire of another year. The imputation is done by following a before-after approach: in the 8th-grade sample, we first look for a value in the 6th-grade questionnaire, or if that is still missing, we rely on the 10th-grade questionnaire; in the 10th-grade sample, we impute from grade 8, or if that is still missing, we go on to grade 6.