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High school students, across the world, prepare for college by participating in shadow education. Despite substantial investments in shadow education, however, little is known about whether it helps students prepare for college. The goal of our study is to provide rigorous evidence about the causal impacts of participating in shadow education on college preparation. We analyze unique data from Russia using a cross-subject student fixed effects model. We find that participating in shadow education positively impacts high-achieving students but not low-achieving students. Participating in shadow education further does not lead students to substitute time away from other out-of-school studies. Instead, the results suggest that low-achieving students participate in low-quality shadow education, which, in turn, contributes to inequality in college access.

JEL classification: I21

Keywords: shadow education, private tutoring, college access, inequality, causal methods

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1. Introduction

All over the world, high school students face considerable pressure when preparing for college. In many countries, high school students must meet competitive entrance requirements for college and elite colleges (Carnoy et al., 2013; Helms, 2008). Even after students meet the entrance requirements, they have to acquire the requisite skills to succeed in and eventually graduate from college (Kuh et al., 2010). Low-achieving students especially face the challenge of not just entering college but making sure that they can persist and not drop out of college (Bettinger and Long, 2009).

Outside of formal schooling, a major way in which high school students prepare for college is by participating in shadow education (e.g. private tutoring and cram courses—Bray, 2007). In many countries, high school students participate in shadow education to improve their chances of doing well on college entrance exams that determine entry into college and elite colleges (S. Lee & Shouse, 2011; Baker and LeTendre, 2005; Bray, 2007; C. Lee et al., 2009; Stevenson & Baker, 1992). High school students may also participate in shadow education when their formal schooling is of low quality and is unable to provide them with the knowledge and skills necessary to succeed in college (Buchmann et al., 2010). Low-achieving high school students, in particular, may be even more likely to participate in shadow education to catch up with their high-achieving peers (Baker et al., 2001). Given its perceived benefits, it is no wonder that the prevalence of shadow education is higher than 50% in a large number of countries from Asia, Africa, the Middle East, and Europe and is growing steadily in the United States and Canada (Bray and Lykins, 2012; Buchmann et al., 2010; Bray, 2006).

Despite the perceived benefits (and consequently the high prevalence) of shadow education, however, there are reasons to believe that it may not help prepare high school students for college. First, high school students may substitute time spent in shadow education for time spent on other learning activities outside of school (e.g. homework, self-study and preparation for exams—see Schmidt, 1983). If students substitute shadow education for other learning activities outside of school that are equally valuable (in terms of knowledge/skill acquisition), their knowledge and skills may not increase. Second, the quality of shadow education may be poor and students may not know that the quality is poor. In other words, even though the quality of education provided is poor, students may continue to take it because they have little information about its quality (Hastings and Weinstein, 2008). Third, similar to formal schooling, not all types of shadow education may be suitable for all types of students. For example, some forms of shadow education may be aimed at helping higher achieving students who already have a strong foundation of academic skills and may not be of much benefit to lower achieving students (Lauer et al., 2003). Owing to a lack of information about the quality of different shadow education programs, students may participate in programs that are not of personal benefit.

The idea that shadow education may not help high school students prepare for college may be surprising to students, families, and policymakers, especially given the high costs of shadow education. It is estimated that (for all levels of schooling) the world will spend over 100 billion US dollars (USD) each year on shadow education by 2018 (Forbes, 2012). Spending on shadow education is high in countries as diverse as Korea (14 billion USD), India (6.4 billion USD), and the United States (5 billion USD—Bray, 2007; Nam, 2007). Such spending reflects the direct costs associated with shadow education (including tuition and materials), but does not even cover the indirect costs (opportunity and travel costs). Given its high costs, if participating in shadow education has negligible impacts on helping high school students prepare for college, then it would prove to be an inefficient use of society's resources.

Not only may participating in shadow education be an inefficient use of society's resources, but it could also contribute to educational inequality. Participating in shadow education could, for example, result in low achievement gains for some subgroups of students compared to others. If low-achieving students gain less from participating in shadow education, for example, then they will be at a disadvantage in preparing for college compared to high-achieving students. Even if low and high-achieving students benefit equally from shadow education, high-achieving students may participate more in shadow education and thereby further surpass the levels of low-achieving students.

Given its potential as a source of both economic inefficiency and educational inequality, it is important to examine whether shadow education, in fact, helps students prepare for college and to what degree. In other words, to what degree does shadow education improve the achievement of high school students? To what degree does shadow education improve the achievement of low- and higher achieving students?

Studies of the impacts of participating in shadow education on the achievement of students (in various levels of schooling) are, unfortunately, inconclusive. Some studies show small, positive impacts of participating in shadow education (0.1 SDs or less) on the academic achievement of students (e.g. Buchman et al., 2010; Byun & Park, 2011; Dang, 2007). There are other studies, however, that indicate that there are no positive impacts from participating in shadow education (e.g. Scott-Little et al., 2002). Studies on the impacts of participating in shadow education on the achievement of low-achieving students are also inconclusive. On the one hand, shadow education may result in substantial learning gains for low-achieving students (Lauer et al., 2003). On the other hand, shadow education may have larger impacts on higher achieving than lower achieving students (Buchmann et al., 2010). A major reason why studies find different impacts from participating in shadow education may be that few of them estimate impacts using rigorous causal research designs (Dang and Rogers, 2008).

The goal of this paper is to provide more rigorous and representative evidence about the causal impacts of participating in shadow education on student achievement. Specifically, we seek to test the impact of participating in shadow education on high school student achievement in high-stakes college entrance exams (and thus the college preparation). We also seek to test whether the impact of participating in shadow education differs for low-achieving (versus higher-achieving) students. We finally seek to examine one reason why participating in shadow education may work for some types of students and not others: that is, whether participating in shadow education crowds out time for other out-of-school studies.

To meet our goal, we rely on a large-scale, representative dataset covering roughly 3,000 high school seniors across 127 schools in 3 regions of Russia in 2010. The dataset contains information on how students prepared for and eventually performed on the two mandatory subjects (Russian language and mathematics) of Russia's high-stakes college entrance exam. We use the cross-subject information in combination with a cross-subject student fixed effects model (Clotfelter et al., 2010), to estimate the impacts of participating in shadow education on high school student achievement.

2. Research Design

2.1. Preparing for the College Entrance Exam in Russia

Perhaps the major reason that high school students in Russia participate in shadow education is because of the substantial competition surrounding college admissions. Even though approximately 80% of high school students in Russia enter college (Education in the Russian Federation, 2012), there are two main reasons why there is substantial competition to enter college in Russia. First, high school students compete to enter elite colleges that ostensibly provide a higher quality of education (and which ostensibly are associated with higher returns). Second, students compete for tuition-free places (versus tuition-paying places) at public colleges (the vast majority of higher education institutions in Russia are public colleges—see Carnoy et al., 2013) to avoid the high costs of attending college. In other words, because the average annual tuition fee at public colleges in Russia is high—roughly equal to 2.9 times average per capita income (see Federal State Statistics Service, 2013)—many students seek to enter the more competitive tuition-free places.

The key factor in college admissions decisions in Russia is student performance on the national entrance exam. In fact, all high school students in Russia must take the national entrance exam or Unified State Examination (USE). The USE is a national test that serves both as the country's high school exit exam and as its college entrance examination. Because it is a high school exit exam, the USE test items are directly linked to the curricula of specific school subjects (and therefore provide a valid measure of students' academic outcomes). Because it is a college entrance exam (that determines entry not only into college but into elite colleges), the USE is also high-stakes. In an effort to get high scores on the exam, students start preparing for the USE (both within school and outside of school through shadow education) at the start of grade 10 or earlier.

The two most important USE subject tests that college-aspiring students must prepare for are Russian language and mathematics. This is because the vast majority of colleges require students to take subject tests in the Russian language and mathematics. The scores on the Russian language and mathematics tests are important in determining whether students can qualify for a particular college and major. The high-stakes nature of the Russian language and mathematics exams, in particular, implies that students take these exams seriously. As we discuss in the Results section below, a major way in which students prepare for the Russian language and mathematics subject tests (in particular) is by participating in shadow education.

2.2. Survey Sample

To estimate the impact of participating in shadow education on student achievement in Russia, we rely on data from a large-scale, representative survey. The survey was conducted in May 2010 in three Russia regions: Pskovskaya and Yaroslavskaya *oblasts* and Krasnoyarsky *krai*. The three regions were chosen because they significantly differ in terms of their geographic location, demographics and economic development, thereby allowing us to make broader inferences about the state of education in Russia. Krasnoyarsky *krai* is located in Siberia. It is one of the largest Russia's regions in terms of territory and population and is one of the most developed in terms of economics. Yaroslavskaya *oblast* is a small region poor with natural resources and is known as Moscow satellite due to its location which enables people flows to Moscow (for a job or higher education) and back. Despite this Yaroslavskaya *oblast* usually takes midrange position in the ratings of economic development. Finally Pskovskaya *oblast* is a small region located to the northwest of the country with a below average economic situation (Russian Regional Socioeconomic Indicators, 2011).

The schools in the dataset were sampled using a stratified random sample design. Eligible schools were those that had at least one 11th grade class. Using official school statistics, eligible schools were first stratified according to *rajon* (administrative district), settlement type (rural, urban, regional center), and school type (regular school, school with advanced study of some subjects, *gymnasia*, *licei* etc.). Schools were then selected within each stratum using simple random sampling. In total, 14.5 percent of schools in Pskovskaya *oblast*, 8.9 percent in Yaroslavskaya *oblast*, and 4.1 percent in Krasnoyarsky *krai* were sampled. Furthermore, in each sampled school, all students in the 11th grade were surveyed. The total sample included 805 students (53 classrooms, 39 schools) from Pskovskaya *oblast*, 986 students (60 classrooms, 42 schools) from Yaroslavskaya *oblast, and* 1,147 students (69 classrooms, 46 schools) from Krasnoyarsky *krai*. Altogether, the dataset contains information on 2,938 final-year (grade 11) students in 127 schools.

2.3. Data

Four groups of respondents were surveyed within each school: grade 11 students, their Russian language and math teachers, and school principals. Students were asked about their participation in shadow education, their previous academic achievements and their individual and family background characteristics. Teachers were asked about their background, professional characteristics and teaching practices. School principals provided information about school characteristics and curricula. Finally, in the summer of 2010, after USE test results were released, each student's individual USE scores in math and Russian language were collected. This information was provided by the regional ministries (departments) of education.

The outcome variable used in our analyses is student achievement as measured by students' performance on the USE. Specifically, our analyses use the scores of the two mandatory USE subject tests (Russian language and mathematics) for each student. We convert the USE scores (which are reported on a 100-point scale for each subject) into z-scores. That is, we subtract each subject test score by the mean of the subject test score (in our sample) and then divide the difference by the standard deviation of the subject test score.

The treatment variable used in our analyses reflects student participation in shadow education. Students reported whether they participated in shadow education during grade 11 for Russian language and mathematics separately. Specifically, students reported whether they participated in any of the following main types of shadow education in Russia: (a) private tutoring (b) "regular USE preparatory courses" (organized by public and private institutions other than colleges), and (c) "college USE preparatory courses" (organized by colleges). The college USE preparatory courses are mainly targeted towards students who plan to enter specific colleges and are taught by college staff. We created a dummy variable that indicates whether students participated in any of the above types of shadow education (equal to one if students participated and zero otherwise).

We also use a large number of student, teacher, class, and school control variables in our analyses. In regards to student variables, we control for students' prior academic achievement in Russian language and mathematics using students' grade 10 marks. The marks (for Russian language and mathematics separately) are on a 5-point scale in theory, but only three points of that scale are used in practice: "three" (satisfied), "four" (good), "five" (excellent). To control prior achievement (marks) we created two dummy variables (one for Russian language and one for mathematics): the dummy variables equal one if students have "good" or "excellent" marks in a subject and zero otherwise.[3]

In regards to class-level variables, we control for "peer effects" and "track". For peer effects, we calculate the average grade 10 marks of each student's in-class peers (leaving out the student) for Russian language and mathematics separately. For track, we create a dummy variable indicating whether the student was in a basic level or advanced level class at the start of grade 11. We again create the track variable for Russian language and mathematics separately. Students in the advanced track receive classroom instruction for more hours per week (3–4.5 hours a week for Russian language, 6–8 hours a week for mathematics) than students in the basic track (1–2 hours a week for Russian language, 4 – 5 hours a week for mathematics).

Our analyses also control for two indicators of teacher quality. First, we control for teacher experience (a series of dummy variables indicating whether the teacher has 10 years or less, 11–20 years, 21–30 years, or 31 plus years of teaching experience). Second, we control for teacher certification level (a series of dummies indicating whether the teacher has no certification, the lowest certification level, the middle certification level, or the highest certification level).

Finally, it is important to note that our analyses do not control for other basic teacher characteristics (across Russian language and mathematics subject teachers) for which there is little

[3] We unfortunately did not have access to other indicators of prior student achievement (besides grade 10 marks). We nonetheless use the marks as controls in our analyses because (a) they are good predictors of USE scores (the grades can be used to differentiate between high and low USE scorers); and (b) they are potentially an important source of information that students use to make decisions about whether or not to participate in shadow education.

or no variation. For example, 99% of the teachers in our sample are female (indeed, over 95% of teachers in Russia at all schooling levels are female— Ministry of Education and Science of the Russian Federation, 2009). We also do not control for teacher age as it is highly correlated with teacher experience.

2.4. Statistical Approach

The main challenge in estimating the causal effect of participating in shadow education on student achievement is selection bias (Dang and Rogers, 2008). Students that participate in shadow education may have different levels of achievement than students that do not participate in shadow education, because there are other factors that are correlated with participation in shadow education and student achievement. Analyses that fail to adequately control for these factors can produce biased estimates of the impact of participating in shadow education on student achievement.

Previous studies have attempted to address the threat of selection bias in various ways. Some studies have invoked the assumption of ignorability and used linear regression with covariate adjustments (Guimarães & Sampaio, 2013; Byun & Park, 2011; Buchmann et al., 2010, Tansel & Bircan, 2005, Stevenson & Baker, 1992) or propensity score matching (Zimmer et al., 2010; Domingue & Briggs, 2009; Hansen, 2004). Dang (2007) attempted to estimate the unbiased impacts of participating in shadow education by using an instrumental variables strategy. Unfortunately, the key assumption underlying the paper's instrumental variable strategy (that the instrumental variables are correlated with student achievement only through participation in shadow education) is difficult to justify. Finally, a few, small-scale randomized experiments from the US have tested the impacts of participating in specific types of shadow education (namely SAT preparation—e.g. Becker, 1990). These studies are of limited external validity, however, since they are small-scale (involving a few hundred individuals, unrepresentative of the wider population of high school students in the United States) and mostly take place before 1990.

We attempt to address the problem of selection bias in our study by using a cross-subjects student fixed effects model (Clotfelter et al., 2010; Kingdon and Teal, 2010; Metzler and Woessmann, 2012). The cross-subjects student fixed effects model uses variation within the same student but across different subjects to identify the impact of shadow education on student achievement. The cross-subject student fixed effect model is derived from the traditional education production function:

$$Y_{is} = \beta_0 + \beta_1 T_{is} + X'_{is}\alpha + Z'_i\delta + u_i + \varepsilon_{is}\ ,\ i = 1, \ldots N,\ s = 1, \ldots S \qquad (1)$$

where Y_{is} is the achievement (USE) score of student i in subject s, T_{is} is the treatment variable (participation in shadow education – yes or no) of student i in subject s; X'_{is} is a vector of student, class, and teacher characteristics that vary across students i and subjects s, Z'_i is a vector of student, class, teacher, and school characteristics that vary across students i only, u_i is a student-specific error term (that represents unobservable variation across students), and ε_{is} is an error term that varies across both students and subjects. The other terms in equation (1) such as β_0, β_1, α, and δ are coefficients (or vectors of coefficients) that reflect the relationship between the variables on the right hand side and student achievement.

Under strict conditions, estimates from the production function in equation (1) can yield causal estimates of the impact of participating in shadow education on student achievement. Specifically, if Y_{is} and T_{is} are uncorrelated with the combined error term ($u_i + \varepsilon_{is}$, where u_i represents unobserved student-level variation and ε_{is} represents unobserved variation across students and subjects), estimates of β_1 would capture the causal effect of participating in shadow (conditional on X'_{is} and Z'_i). Unfortunately, unobserved student-level variation (for example, student motivation) is often jointly correlated with participation in shadow education and academic achievement.

The cross-subjects student fixed effects model attempts to control for the problematic correlation between the portion of the error term that varies across students but not across subjects (u_i) and the treatment and outcome variables. By averaging equation (1) across subjects (which we call the "averaged equation") and then subtracting the averaged equation from equation (1), the cross-subjects student fixed effects model eliminates the confounding influence of u_i (and $Z'_i\delta$):

$$Y_{is} - \overline{Y_i} = \beta_1(T_{is} - \overline{T_i}) + (X_{is} - \bar{X}_i)\alpha + (\varepsilon_{is} - \overline{\varepsilon_i}), \qquad (2)$$

where $\overline{Y_i} = \frac{1}{S}\sum_{s=1}^{S} Y_{is}$, $\bar{X}_i = \frac{1}{S}\sum_{s=1}^{S} X_{is}$, $\overline{T_i} = \frac{1}{S}\sum_{s=1}^{S} T_{is}$, $\overline{\varepsilon_i} = \frac{1}{S}\sum_{s=1}^{S} \varepsilon_{is}$.

The above model (2) produces unbiased estimates of β_1 under a few assumptions. The first assumption is that coefficients for each variable are equal across the two subjects (Dee, 2005). This implies that the way in which participation in shadow education (and other characteristics that vary across subjects) affects student achievement is the same across subjects. The second assumption is that the remaining error term ($\varepsilon_{is} - \overline{\varepsilon_i}$) in equation (2) is uncorrelated with the treatment ($T_{is} - \overline{T_i}$). This means that unobserved student, classroom, or teacher characteristics that vary across students and subjects should not be jointly correlated with participation in shadow education and student achievement (Schwerdt and Wuppermann, 2011). To reduce the potential confounding influence of unobserved variation across subjects, we control for a number of important pre-treatment, cross-subject factors such as student grade 10 marks, peer grade 10 marks, student's track, and cross-subject teacher characteristics (see subsection 2.3 above).

3. Results

3.1. The Determinants of Participating in Shadow Education

According to our data, a high proportion of grade 11 students participate in shadow education. Specifically, 47.9% and 54.6% of grade 11 students said that they participate in shadow education in Russian language and mathematics (tables omitted for the sake of brevity). Such a high rate of participation in shadow education, in general, and for both the Russian language and mathematics tests, in particular, is not surprising since the vast majority of colleges consider the results from these two USE subject tests for college admissions.

Although a high proportion of students participate in shadow education, the types of students that participate in shadow education are systematically different from the types of students that do not participate (see Table 1, Column 9). Students that participate in shadow education are more likely to be from a higher socioeconomic background (Table 1, Row 5) and are less likely to be from rural areas (Table 1, Row 7). They are also more likely to be from higher quality schools, at least as measured by whether students attend an elite school or a slightly larger school (Table 1, Rows 8-9). Students that participate in shadow education are furthermore more likely to expect to attend college (Table 1, Row 7), have more books in their homes (Table 1, Row 2), and are somewhat younger than their peers that do not participate in shadow education (Table 1, Row 1). Finally, the average differences between students that participate and do not participate in shadow education are similar no matter if we look at shadow education targeted at the Russian language or shadow education targeted at mathematics (Table 1, Columns 3 and 6).

Because students that participate in shadow education differ in observed characteristics, we worry that they may differ in unobserved characteristics as well. Estimates from standard regression procedures that would seek to determine the impact of shadow education on student achievement would be unable to control for all of the unobserved characteristics that are constant within the student. The estimates would therefore be biased. In an attempt to address the potential problems associated with selection bias, we next present estimates from the cross-subject student fixed effects model.

Table 1. Characteristics of Students Participating in Shadow Education in Grade 11
(in Russian Language, in Math, and in Both Subjects Combined)

	Took shadow education (Russian Language)			Took shadow education (Math)			Took shadow education (Either Subject)		
	yes	**no**	**difference**	**yes**	**no**	**difference**	**yes**	**no**	**difference**
Male	0.41	0.40	0.01	0.39	0.42	-0.03	0.40	0.43	-0.03
Born in 1993 or after (yes/no)	0.45	0.39	0.06**	0.44	0.39	0.05**	0.45	0.37	0.08**
Books in the home (< 100 = yes, ≥100 =no)	0.5	0.57	-0.07***	0.51	0.56	-0.05**	0.50	0.59	-0.09***
Living with both parents (yes/no)	0.67	0.67	-0.00	0.67	0.66	0.01	0.67	0.67	0.00
Siblings at home (yes/no)	0.4	0.44	-0.04**	0.41	0.45	-0.04**	0.40	0.45	-0.05**
Socioeconomic status (family asset index)	0.14	-0.14	0.28***	0.12	-0.15	0.27***	0.11	-0.19	0.30***
Expects to attend college in grade 10 (yes/no)	0.35	0.27	0.08***	0.33	0.28	0.05**	0.33	0.25	0.08***
Rural (yes/no)	0.12	0.22	-0.10***	0.13	0.23	-0.10***	0.12	0.25	-0.13***
Attending elite school (yes/no)	0.37	0.23	0.14***	0.35	0.22	0.13***	0.36	0.18	0.18***
School size (# students)	640.77	563.11	77.66***	649.55	541.10	108.45***	648.13	517.55	130.58***
Grade 10 marks (4, 5 = yes; 2, 3 = no)	0.62	0.59	0.03	0.55	0.51	0.04	--	--	--
Class' grade 10 marks (4, 5 = yes; 2, 3 = no)	0.43	0.34	0.09***	0.37	0.27	0.10***	--	--	--
Took advanced class (yes/no)	0.22	0.18	0.04	0.37	0.37	0.00	--	--	--

Cluster-robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

3.2. The Impacts of Participating in Shadow Education on High School Student Achievement

According to our cross-subject student fixed effects model estimates, participating in shadow education has a negligible impact on student (USE) achievement (Table 2). When we only control for unobserved student characteristics that are constant across subjects (and not for other cross-subject characteristics), we find that the impact of participating in shadow education is zero in magnitude (Table 2, Column 1). The result is furthermore not statistically significant, even at the 10% level. After we control for an array of cross-subject control variables (such as students' marks in grade 10, peer grades, participation in advanced tracks, participation in additional in-school classes, and teacher characteristics) in the model, the impact of participating in shadow education barely increases to 0.02 standard deviations (Table 2, Column 2). Again, the result is not statistically significant at even the 10% level. It thus appears from these results that participating in shadow education has no impact on student achievement.

When we examine the impact of participating in shadow education for low-achieving and high-achieving students, however, the results are more nuanced (Table 3). According to our (covariate-adjusted) results in Table 3 (Column 1), participating in shadow education increases the achievement of high-achieving students by 0.13 standard deviations. The estimate is furthermore statistically significant at the 5% level. By contrast, participating in shadow education seems to have a slightly negative impact of 0.06 standard deviations on the achievement of low-achieving students. The estimate is not statistically different from zero, however. Taken together, the results imply that participating in shadow education benefits students from high-achieving backgrounds but does not benefit students from low-achieving backgrounds.

Table 2. The Impact of Shadow Education on Students' USE Achievement
(Cross-Subject Student Fixed Effects Model)

	(1)	(2)
Participated in shadow education (y/n)	-0.00	0.02
	(0.04)	(0.04)
Grade 10 marks (4 or 5 = yes, 2 or 3 = no)		0.36***
		(0.03)
Advanced subject study (y/n)		0.17***
		(0.06)
Class' grade 10 marks (4 or 5 = yes, 2 or 3 = no)		-0.27
		(0.20)
Teacher experience: <=10 years (y/n)		0.03
		(0.09)
Teacher experience: 21-30 years (y/n)		0.01
		(0.06)
Teacher experience: >31 years (y/n)		-0.02
		(0.06)
Teacher qualification, lowest category (y/n)		-0.04
		(0.07)
Teacher qualification, highest category (y/n)		0.07
		(0.05)
Took additional classes in school (y/n)		0.01
		(0.05)
Constant	0.00	-0.20**
	(0.02)	(0.10)
Observations	5,876	5,872
R-squared	0.00	0.06
Number of students	2,938	2,936

Cluster-robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table 3. Impacts of Shadow Education on the USE Achievement of Students with High Marks and of Students with Low Marks
(Cross-Subject Student Fixed Effects Model)

	(1) students with high grade 10 marks	(2) students with low grade 10 marks
Participated in shadow education (y/n)	0.13**	-0.06
	(0.05)	(0.06)
Advanced subject study (y/n)	0.22***	0.15**
	(0.07)	(0.07)
Class' grade 10 marks (4 or 5 = yes, 2 or 3 = no)	-0.07	-0.43
	(0.22)	(0.28)
Teacher experience: <=10 years (y/n)	0.04	-0.06
	(0.12)	(0.10)
Teacher experience: 21-30 years (y/n)	0.08	-0.09
	(0.08)	(0.07)
Teacher experience: >31 years (y/n)	-0.02	-0.07
	(0.09)	(0.09)
Teacher qualification, lowest category (y/n)	-0.08	0.01
	(0.10)	(0.07)
Teacher qualification, highest category (y/n)	0.06	0.04
	(0.07)	(0.05)
Took additional classes in school (y/n)	0.00	0.01
	(0.06)	(0.07)
Constant	0.40***	-0.54***
	(0.12)	(0.10)
Observations	2,626	1,826
R-squared	0.04	0.02
Number of students	1,313	913

Cluster-robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Notes:
"students with high grade 10 marks" refers to students who had a mark of 4 or 5 on both Russian language and mathematics in grade 10
"students with low grade 10 marks" refers to students who had a mark of 2 or 3 on both Russian language and mathematics in grade 10

3.3. Does Shadow Education Cause Students to Substitute Away from their Studies?

Although our data do not allow us to investigate all the possible reasons why shadow education helps high-achieving students but does not help low-achieving students, we examine whether shadow education creates different out-of-school study behaviors for the two types of students. Specifically, we investigate whether the additional input of time required from participating in shadow education differentially causes high and low-achieving students to substitute time away from their other out-of-school studies. Towards this end, we apply the same cross-subject fixed effects model (as in equation 2) and examine whether participating in shadow education impacts (a) whether (high and low-achieving) students prepare for the USE on their own or not; and (b) whether students always complete their homework or not.

According to our estimates, we find little evidence that participating in shadow education causes students to substitute time away from their other out-of-school studies. The impact of participating in shadow education on whether high-achieving students prepare for the USE on their own is zero (Table 4, Column 1). Although it appears that low-achieving students may be slightly less likely to prepare for the USE on their own if they participate in shadow education, the impact estimate has a small magnitude (-0.04) and is not statistically different from zero (Table 4, Column 2). Similarly, the impact of participating in shadow education on the likelihood of whether high-achieving students always complete their homework is also zero in magnitude (and not statistically different from zero—Table 5, Column 1). Low-achieving students are also just as likely to always complete their homework, whether or not they participate in shadow education (impact estimate of -0.02 and not statistically different from zero—see Table 5, Column 2). In summary, we find little evidence that shadow education helps high-achieving students because it causes them to spend more time on their other studies. We also find little evidence that shadow education fails to help low-achieving students because it causes them to spend less time on their other out-of-school studies.

Table 4. The Impact of Shadow Education on Whether Students Prepare for the USE on Their Own—for Subgroups of Students with High and Low Marks
(Cross-Subject Student Fixed Effects Model)

	(1) students with high grade 10 marks	(2) students with low grade 10 marks
Participated in shadow education (y/n)	-0.00	-0.04
	(0.03)	(0.03)
Advanced subject study (y/n)	0.02	-0.00
	(0.02)	(0.02)
Class' grade 10 marks (4 or 5 = yes, 2 or 3 = no)	-0.03	-0.03
	(0.05)	(0.06)
Teacher experience: <=10 years (y/n)	0.01	-0.02
	(0.03)	(0.03)
Teacher experience: 21-30 years (y/n)	0.01	0.02
	(0.02)	(0.02)
Teacher experience: >31 years (y/n)	0.01	-0.01
	(0.02)	(0.02)
Teacher qualification, lowest category (y/n)	-0.01	-0.01
	(0.02)	(0.03)
Teacher qualification, highest category (y/n)	-0.00	-0.00
	(0.02)	(0.02)
Took additional classes in school (y/n)	0.05	0.09***
	(0.03)	(0.03)
Constant	0.81***	0.70***
	(0.04)	(0.04)
Observations	2,626	1,826
R-squared	0.01	0.02
Number of students	1,313	913

Cluster-robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Notes:
"students with high grade 10 marks" refers to students who had a mark of 4 or 5 on both Russian language and mathematics in grade 10
"students with low grade 10 marks" refers to students who had a mark of 2 or 3 on both Russian language and mathematics in grade 10

Table 5. The Impact of Shadow Education on Whether Students Always Complete Homework—for Subgroups of Students with High and Low Marks
(Cross-Subject Student Fixed Effects Model)

	(1) students with high grade 10 marks	(2) students with low grade 10 marks
Participated in shadow education (y/n)	-0.00	-0.02
	(0.03)	(0.03)
Advanced subject study (y/n)	0.06**	-0.02
	(0.02)	(0.02)
Class' grade 10 marks (4 or 5 = yes, 2 or 3 = no)	-0.02	0.09
	(0.07)	(0.05)
Teacher experience: <=10 years (y/n)	0.01	0.07*
	(0.04)	(0.04)
Teacher experience: 21-30 years (y/n)	0.06*	0.01
	(0.03)	(0.02)
Teacher experience: >31 years (y/n)	0.04	-0.00
	(0.04)	(0.03)
Teacher qualification, lowest category (y/n)	-0.04	-0.05*
	(0.04)	(0.03)
Teacher qualification, highest category (y/n)	0.04	0.04
	(0.03)	(0.03)
Took additional classes in school (y/n)	0.13***	0.07
	(0.04)	(0.04)
Constant	0.35***	0.13***
	(0.06)	(0.04)
Observations	2,626	1,826
R-squared	0.04	0.02
Number of students	1,313	913

Cluster-robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Notes:
"students with high grade 10 marks" refers to students who had a mark of 4 or 5 on both Russian language and mathematics in grade 10
"students with low grade 10 marks" refers to students who had a mark of 2 or 3 on both Russian language and mathematics in grade 10

4. Discussion and Conclusion

A large proportion of high school students, across a wide variety of countries, participate in shadow education (Bray, 2007). Although many studies have attempted to estimate the causal impact of participating in shadow education on student achievement, few large-scale studies have adequately addressed threats arising from selection bias (Dang and Rogers, 2008). In this study, our goal was to analyze the causal impact of shadow education on high school student achievement using a cross-subject student fixed effects model that not only controls for unobserved heterogeneity that is constant across subjects within the same student but also controls for student, class, and teacher level cross-subject covariates. We not only estimated results for high school students, in general, but also explored whether the impacts of participating in shadow education differed for high and low-achieving students separately.

Our findings show that participating in shadow education has no positive impact on the achievement of low-achieving students, but rather has a positive and significant impact on the achievement of high-achieving students. In other words, our results indicate that shadow education gives high-achieving students an additional advantage over low-achieving students that are competing to enter college and elite colleges. Since participating in shadow education only appears to benefit high-achieving students (who, according to our results in Table 1, are also from higher socioeconomic backgrounds), it appears to lead to greater educational and social inequality. The results further suggest that low-achieving students are not receiving the main purported benefits of shadow education (college preparation), even though they may be investing substantial sums into private tutoring or after-school courses.

The finding that low-achieving students invest in shadow education, even though they receive no benefit, may be surprising. Two possible explanations for the result are that low-achieving students (and their parents) may invest in shadow education and not realize that the quality of shadow education is poor on average (in that it does not help them to increase their achievement). Another possible explanation, and one that we tested, is that students might also think that once they participate in shadow education, they do not need to spend as much time on their other out-of-school studies in preparation for college. Although, it is difficult to measure a "zero effect" of shadow education on time spent on other out-of-school studies with great precision, our results do suggest that participating in shadow education causes students to spend less time on their other out-of-school studies. In other words, the effects of shadow education (for either high or low-achieving students) do not appear to be mitigated by students substituting time away from other studies. Barring other explanations, we therefore conclude that, on average, low-achieving students lack information about the quality (or suitability) of the shadow education programs they attend. Policymakers that are concerned about inefficiency in the provision of shadow education (in helping low-achieving students), as well as the educational inequality that arises from differences in the impacts of shadow education across low and high achieving students, may therefore wish to find ways of providing this information to low-achieving students.

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