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Does shadow education help students prepare for college? Evidence from Russia

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ABSTRACT

Given the lack of causal evidence from developing countries, we examine the impact of participating in shadow education (private tutoring or other fee-based academic activities outside of formal schooling) on high school student achievement. Specifically, we analyze a unique dataset from Russia using a cross-subject student fixed effects model. We find that shadow education only positively impacts the achievement of high-achieving (and not low-achieving) students. Shadow education also does not lead students to substitute time away from their studies. Instead, our findings suggest that low-achieving students participate in low-quality shadow education which, in turn, contributes to inequality in college access.

An important way that high school students compete to enter college and, especially selective colleges, is by hiring private tutors or attending fee-based academic activities outside of formal schooling (Bray, 2007). Such types of fee-based, out-of-school activities are collectively known as "shadow education" (Bray, 2007). Students (and their parents) pay for shadow education with the hopes that it will help them get better grades and score relatively higher than their peers on college entrance exams (Lee and Shouse, 2011; Baker and LeTendre, 2005; Bray, 2007; Lee et al., 2009; Stevenson and Baker, 1992). Low-achieving high school students, in particular, may believe that participating in shadow education can help them to be more competitive with their high-achieving peers (Baker et al., 2001). Because the number of students that have completed high school and are competing to enter college has grown markedly in developing countries in the last two decades, the market for shadow education has also grown rapidly (Bray and Lykins, 2012; Buchmann et al., 2010; Silova et al., 2006; Bray, 2006).

Despite its perceived benefits and growing prevalence, the degree to which shadow education can help students meet college entrance requirements is unclear. In theory, high school students can substitute time spent in shadow education for time spent on other learning activities outside of school, such as homework, self-study and preparation for entrance exams (Carnoy et al., 2013; Schmidt, 1983). If these other learning activities are equally valuable in terms of helping students meet college entrance requirements, students may not need to invest in shadow education. Furthermore, some students may lack information on the quality of various shadow education offerings and may therefore participate in programs that are not beneficial. Indeed, the quality and scope of shadow education programs appear to vary greatly (Lauer et al., 2003). Research has shown more generally that low-achieving students are more likely to lack information about the quality of education programs (Hastings and Weinstein, 2008).

The possibility that shadow education may not help some students meet college entrance requirements may be counterintuitive, given how much students and their families spend on it. It is estimated that by 2018, students and their families worldwide will spend—at all levels of schooling—over $100 billion annually on shadow education (Forbes, 2012). If participating in shadow education has a relatively small academic payoff, then spending such large sums would seem to be a highly inefficient use of resources. If spending on shadow education fails to benefit certain types of students—for example, low-achieving or economically disadvantaged students—it may not only be inefficient but also may contribute to social inequality (Silova et al., 2006). The strikingly large investments made in shadow education combined with its potential implications for economic efficiency and social inequality, suggests that it is important to examine the

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consequences of participating in shadow education for different types of students.

Unfortunately, there is little evidence to date about whether shadow education helps students in general, or disadvantaged students, in particular, fulfill college entrance requirements. Specifically, few studies from developing countries use rigorous causal research designs to measure the impact of shadow education on student achievement during primary, junior high, and high school (Dang and Halsey Rogers, 2008), or to measure the impact on the ability of students to fulfill end-of-high-school competitive college entrance requirements.

Given the dearth of evidence, our paper has two major goals. The first is to examine the causal impact of participating in shadow education on the achievement of high school students. The second goal is to examine the differential impacts of participating in shadow education on the achievement of low versus high-achieving high school students. In addition to these two major goals, we also explore why participating in shadow education may or may not impact high school student achievement.

To fulfill our goal, we examine the impacts of participating in shadow education on the college entrance exam performance of a representative sample of approximately 3000 high school seniors in 127 schools from three regions of Russia. Russia is a good case to study since students in the country are required to take a national college entrance exam at the end of high school. Similar to other large developing countries such as China, India, and Brazil (Carnoy et al., 2013), performing well on the exam is often the main, and usually only, requirement for entering college and selective colleges. In light of its high-stakes nature, a large proportion of high school students in Russia participate in shadow education to prepare for the exam.

We seek to identify the causal impacts of participating in shadow education on student performance by utilizing a cross-subject student fixed effects design. This design has been used in a number of recent studies (for example, Zakharov et al., 2014; Van Klaveren, 2011; Schwerdt and Wuppermann, 2011; Clotfelter et al., 2010; Kingdon and Teal, 2010; Dee, 2005, 2007). We examine the impacts of two major types of shadow education on exam results: (a) college preparatory courses and (b) private tutoring. We also examine whether participating in college preparatory courses and private tutoring has different impacts on low-achieving and high-achieving students. Finally, we examine a possible reason why participating in shadow education may work for some students and not others: that is, we test the hypothesis that participating in shadow education crowds out time for other out-of-school studies.

1. Background

1.1. Previous studies that estimate the impacts of shadow education

Studies of the impacts of participating in shadow education on the performance of students (in various levels of schooling) show mixed results. Several studies argue that there are positive associations or impacts from participating in various types of shadow education. For example, Buchmann et al. (2010) find positive correlations between preparatory courses or private tutoring and SAT achievement in the United States. Guimarães and Sampaio (2013) find strong, positive correlations between private tutoring and college entrance exam results in Brazil. Dang (2007) finds much smaller but still positive impacts of private tutoring on the achievement of lower secondary students in Vietnam. Kuan (2011) also finds small but positive impacts of preparatory courses (i.e. attending cram schools) on the achievement of grade 9 students in Taiwan.

Other studies, however, show that there are few, if any, positive impacts from participating in shadow education. For example, Byun and Park (2011) find no significant relationship between private tutoring and SAT achievement among high school students in the United States. Gurun and Millimet (2008) actually find negative impacts of private tutoring on university placement in Turkey.

Studies on the impacts of participating in shadow education on the performance 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 (or higher socioeconomic status than lower socioeconomic status) students (Buchmann et al., 2010; Domingue and Briggs, 2009).

One reason why studies find different impacts from participating in shadow education may be that they vary in the degree that they estimate impacts using rigorous causal research designs (Dang and Halsey Rogers, 2008). The main challenge in estimating the causal effect of participating in shadow education on student performance is selection bias. 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 performance (Domingue and Briggs, 2009).

Previous studies have attempted to address the threat of selection bias in various ways. Some studies have invoked the assumption of selection on observables and used linear regression with covariate adjustments (Guimarães and Sampaio, 2013; Byun and Park, 2011; Buchmann et al., 2010; Tansel and Bircan, 2005; Stevenson and Baker, 1992) or propensity score matching (Kuan, 2011; Zimmer et al., 2010; Domingue and 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 outcomes only through participation in shadow education—is difficult to justify. Finally, a few, small-scale randomized experiments in the United States 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. In contrast to earlier studies (and as explained below in Section 3), we attempt to deal with selection bias by using a cross-subject student fixed effects model (see, for example, Zakharov et al., 2014; Van Klaveren, 2011; Schwerdt and Wuppermann, 2011; Clotfelter et al., 2010; Kingdon and Teal, 2010; Dee, 2005, 2007).

1.2. Preparing for the college entrance exam in Russia

Since the collapse of socialism, the market for shadow education has been growing rapidly in Russia (and indeed in the rest of Eastern Europe and Central Asia—Kozar, 2013; Silova, 2010; Silova et al., 2006). By 2012, the annual amount of spending on shadow education reportedly exceeded 800 million US dollars (Rusetskaya, 2013). Approximately 25–30% of this spending was at the high school level, up 23% from the previous year (Rusetskaya, 2013).

A major reason for the popularity of shadow education at the high school level in Russia is the substantial competition surrounding college admissions (Kozar, 2013). Even though approximately 80% of high school students in Russia eventually enter college (National Research University Higher School of Economics, 2012), there are two main reasons why there is substantial competition to enter college in Russia (and other post-socialist bloc countries—Silova, 2010). First, high school students compete to enter elite colleges that ostensibly provide a higher quality of education, and which are thus 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)—most students, including students from different socioeconomic backgrounds and achievement levels, seek to enter the more competitive tuition-free places.

The key factor in college admissions decisions in Russia is student performance on the national college 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. As a result, virtually all academic high school students in Russia take the USE. 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.

Although shadow education can come in many forms (Bray, 2007), students preparing for the USE usually participate in two types of shadow education: (a) private tutoring (organized by private companies or individuals) and (b) college or "USE" preparatory courses organized by private agencies as well as colleges. Both types of shadow education are geared toward helping students pass specific subject tests of the USE.

The USE is comprised of mandatory and optional subject tests. The two mandatory subject tests that college-aspiring students must prepare for are Russian language and mathematics.[2] Scores on the Russian language and mathematics tests are important for determining whether students can qualify for particular colleges and majors. As we discuss in the Section 3, a major way in which students prepare for the mandatory Russian language and mathematics subject tests is by participating in shadow education.

2. Research design

2.1. Survey sample

To estimate the impact of participating in shadow education on student performance 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. It is known as a Moscow "suburb." because of its location, which allows workers and students to commute to Moscow. Despite this, Yaroslavskaya *oblast* falls in the midrange of Russian economic development rankings. Finally, Pskovskaya *oblast* is a small region located in the northwest of the country with a below average economic conditions (Federal State Statistics Service, 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, such as *gymnasiums* and *lycea*). 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* 1147 students (69 classrooms, 46 schools) from Krasnoyarsky *krai*. Altogether, the dataset contains information on 2936 final-year (grade 11) students in 127 schools.

2.2. Data

Three types of respondents were surveyed within each school: a randomly sampled class of students in their final year of high school (grade 11), the Russian language and math teachers associated with this class (two teachers per class), and the high 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. Each student's USE scores were successfully matched (nearly 100%) to the information from the student survey questionnaires.

The outcome variable used in our analyses is student 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.

The treatment variables used in our analyses reflect student participation in shadow education during grade 11 for Russian language and mathematics separately. Specifically, students reported whether they participated in either one or both of the two main types of shadow education: (a) private tutoring and/or (b) college (USE) preparatory courses organized by private agencies or universities. Approximately 47.9% of students in our sample participated in Russian language shadow education—29.9% participated in private tutoring and 28.2% in college preparatory courses. Approximately 54.6% of students in our sample participated in math shadow education—39.0% in private tutoring and 28.1% in college preparatory courses.

We created dummy variables for whether students participated in each of the two types of shadow education and for each subject

[2] In fact, in 2010, 98.3% of USE participants took the Russian language subject exam and 94.6% took the math subject exam. The participation rate in other subjects fell dramatically after these two subjects. In regards to the three next most popular subject exams, only 48% of USE participants took the social science subject exam, 22.1% took the physics subject exam, and 19% took the history subject exam (Federal Institute for Measurement in Education, 2010).

separately (equal to one if students participated and zero otherwise). Like most studies (see, for example Buchmann et al., 2010; Byun and Park, 2011; Domingue and Briggs, 2009; Guimarães and Sampaio, 2013), our data is limited in that we do not have information on the amount of hours or money students spent in each type of shadow education. Similar to most other studies (see, for example, Buchmann et al., 2010; Byun and Park, 2011; Dang, 2007; Hansen, 2004; Gurun and Millimet, 2008), we also do not have any information about the quality of each type of shadow education. Nonetheless, by separating shadow education into private tutoring and college preparatory courses, we can make the important qualitative distinction of how different types of shadow education impact student performance.

We also use a large number of student, teacher, class, and school control variables in our analyses. With regard 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 four points of that scale are used in practice: "two" (unsatisfactory), "three" (satisfactory), "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] We created these dummy variables to account for the distribution of student marks in our sample: only 10.6% of students had a "five" in Russian language and only 12.3% had a "five" in math. By controlling for students' grade 10 marks in our analysis we are able to at least partially control for a priori differences in student motivation.

In regards to class-level variables, we control for "peer effects", "track", and "additional classes in school". For peer effects, we calculate the average grade 10 marks of each student's in-class peers (leaving out the observed 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 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 h a week for Russian language, 6–8 h a week for mathematics) than students in the basic track (1–2 h a week for Russian language, 4–5 h a week for mathematics). Finally, we control for whether students participated in additional USE preparatory classes in school. We do not regard these additional in-school classes as shadow education since they are part of the student's formal education and are not organized for profit-making purposes (Bray, 2007).

Our analyses also control for 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. We do not control for other basic teacher characteristics for which there is little 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 Russia, 2009). We also do not control for teacher age, as it is highly correlated with teacher experience.

[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.

2.3. Statistical approach

We attempt to address the problem of selection bias in our study by using a cross-subject student fixed effects model, such as that used by Zakharov et al. (2014), Van Klaveren (2011), Schwerdt and Wuppermann (2011), Clotfelter et al. (2010), Kingdon and Teal (2010), Dee (2005, 2007). In this model, we compare outcomes within the same student in different conditions (in different subjects), controlling for other factors that may differ across these conditions (subjects). By comparing outcomes within the same student, the model successfully eliminates all confounding factors that are unique to the student and which do not vary across subjects. By also controlling for subject-specific factors within the student, we further account for the remaining factors which may vary even within the student but across subjects. Taken together, we arguably control for a much greater number of potentially confounding factors than past studies.

The cross-subject student fixed effect model is derived from the traditional education production function:

$$Y_{is} = \beta_0 + \beta_1 T_{is} + X'_{is}\alpha + Z'_i\delta + u_i + \epsilon_{is}, \quad i = 1, \ldots N, s = 1, \ldots S \tag{1}$$

where Y_{is} is the exam (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 Eq. (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 performance.

Under strict conditions, estimates from the production function in Eq. (1) can yield causal estimates of the impact of participating in shadow education on student performance. 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 or self-confidence) is often jointly correlated with participation in shadow education and academic performance.

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 Eq. (1) across subjects (which we call the "averaged equation") and then subtracting the averaged equation from Eq. (1), the cross-subjects student fixed effects model eliminates the confounding influence of u_i (and $Z_i\delta$):

$$Y_{is} - Y_{\bar{i}} = \beta_1(T_{is} - T_{\bar{i}}) + (X_{is} - X_{\bar{i}})\alpha + (\epsilon_{is} + \epsilon_{\bar{i}}), \tag{2}$$

where $Y_{\bar{i}} = 1/S\sum_{s=1}^{S} Y_{is}$, $X_{\bar{i}} = 1/S\sum_{s=1}^{S} X_{is}$, $T_{\bar{i}} = 1/S\sum_{s=1}^{S} T_{is}$, $\epsilon_{\bar{i}} = 1/S\sum_{s=1}^{S} \epsilon_{is}$.

As discussed in Van Klaveren (2011), Clotfelter et al. (2010), Kingdon and Teal (2010), and Dee (2005, 2007), the above model (2) produces unbiased estimates of β_1 under substantially less restrictive assumptions. The first assumption is that the way in which participation in shadow education affects student

Table 1
Comparing the characteristics of grade 11 students participating and not participating in shadow education (Russian language, math, and 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 in Russian/math (4, 5 = yes; 2, 3 = no)	0.62	0.59	0.03	0.55	0.51	0.04	–	–	–
Class' grade 10 marks in Russian/math (4, 5 = yes; 2, 3 = no)	0.43	0.34	0.09^{**}	0.37	0.27	0.10^{**}	–	–	–
Advanced subject study (yes/no)	0.22	0.18	0.04	0.37	0.37	0.00	–	–	–
Took additional classes in Russian/math in school (y/n)	0.71	0.70	0.01	0.77	0.73	0.04	–	–	–
Math USE (*z*-score)	0.10	−0.10	0.20^{**}	0.07	−0.08	0.15^{**}	0.09	−0.15	0.24^{**}
Russian language USE (*z*-score)	0.09	−0.09	0.18^{**}	0.06	−0.07	0.13^{*}	0.09	−0.15	0.24^{**}

* $p < 0.05$.
** $p < 0.01$.

performance is similar across subjects. This assumption is more likely to hold in our case (as compared to previous studies), since the majority of (multiple choice and short-answer format) items on the Russian language or mathematics subject exams can be answered by applying basic subject knowledge and test-taking strategies (Zakharov et al., 2014). Furthermore, in an attempt to control for the fact that shadow education in one subject may influence student performance more than the other, we also check whether our findings are robust to adding a "subject" dummy variable (Russian language = 1 and math = 0) to Eq. (2).[4]

The second assumption is that the remaining error term ($\epsilon_{is}-\epsilon_{i\bar{s}}$) in Eq. (2) is uncorrelated with the treatment ($T_{is}-T_{i\bar{s}}$). This means that unobserved student, classroom, or teacher characteristics that vary across the two subjects should not be jointly correlated with participation in shadow education and student performance (Schwerdt and Wuppermann, 2011). Although the identification strategy controls for all student, classroom, and school factors that do not vary across subjects (within students), we further reduce the potential confounding influence of unobserved variation across subjects by controlling for a number of important pre-treatment, cross-subject factors that are often used in value-added modeling (Kane et al., 2013). The cross-subject factors include student grade 10 marks, peer grade 10 marks, student's track, additional in-school classes and cross-subject teacher characteristics (see Section 2.2).

3. Results

3.1. What types of students participate 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. 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.

[4] The results from model with the additional subject dummy are virtually identical to those without the subject dummy (results are omitted for the sake of brevity but are available upon request).

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 6) and are less likely to be from rural areas (Table 1, Row 8). 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 9–10). 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 3), and are somewhat younger than their peers that do not participate in shadow education (Table 1, Row 2). 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, they may differ in unobserved characteristics as well. Estimates from OLS regression or propensity score matching analyses would be unable to control for unobserved student characteristics and would therefore lead to biased estimates of the impact of shadow education on student performance. As discussed in Section 2.3, we control for unobserved (student-level) characteristics through our cross-subject student fixed effects model. The results of this model are presented immediately below.

3.2. The impacts of participating in shadow education on student performance

According to our cross-subject student fixed effects model estimates, participating in shadow education has a negligible impact on the USE performance of the average high school student (Table 2). The impact of participating in college preparatory courses is only slightly above zero (Table 2, Columns 1 and 3). The impact of participating in private tutoring is also negligibly small (Table 2, Columns 2 and 3). Furthermore, none of these results are statistically different from zero at the 5% level. It thus appears from these results that participating in shadow education has no impact on the performance of the average student.

Table 2
The impact of shadow education on student (USE) achievement (cross-subject student fixed effects model).

	(1)	(2)	(3)
College preparatory course (y/n)	0.05		0.05
	(0.04)		(0.04)
Private tutoring (y/n)		0.02	0.02
		(0.04)	(0.04)
Took additional classes in school (y/n)	0.01	0.01	0.01
	(0.05)	(0.05)	(0.05)
10th grade grade	0.36**	0.36**	0.36**
	(0.03)	(0.03)	(0.03)
Advanced subject study (y/n)	0.17**	0.17**	0.17**
	(0.06)	(0.06)	(0.06)
Class' grade 10 marks (4 or 5 = yes, 2 or 3 = no)	−0.27	−0.27	−0.27
	(0.20)	(0.20)	(0.20)
Teacher experience: ≤10 years (y/n)	0.03	0.03	0.03
	(0.09)	(0.09)	(0.09)
Teacher experience: 21–30 years (y/n)	0.01	0.01	0.01
	(0.06)	(0.06)	(0.06)
Teacher experience: >31 years (y/n)	−0.02	−0.02	−0.02
	(0.06)	(0.07)	(0.06)
Teacher qualification: lowest category (y/n)	−0.04	−0.04	−0.04
	(0.07)	(0.07)	(0.07)
Teacher qualification: highest category (y/n)	0.07	0.07	0.07
	(0.05)	(0.05)	(0.05)
Constant	−0.20*	−0.20*	−0.21*
	(0.09)	(0.10)	(0.10)
Observations	5872	5872	5872
R-squared	0.06	0.06	0.06
Number of students	2936	2936	2936

Cluster-robust standard errors in parentheses:
* $p < 0.05$.
** $p < 0.01$.

Table 3
The impact of shadow education on high and low achieving students (cross-subject student fixed effects model).

	High-achieving students[a] (1)	Low-achieving students[b] (2)
College preparatory course (y/n)	0.15*	−0.01
	(0.06)	(0.07)
Private tutoring (y/n)	0.05	0.04
	(0.05)	(0.06)
Took additional classes in school (y/n)	−0.01	0.01
	(0.06)	(0.07)
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)	−0.08	−0.41
	(0.22)	(0.29)
Teacher experience: ≤10 years (y/n)	0.05	−0.06
	(0.13)	(0.10)
Teacher experience: 21–30 years (y/n)	0.08	−0.09
	(0.08)	(0.07)
Teacher experience: >31 years (y/n)	−0.01	−0.07
	(0.08)	(0.09)
Teacher qualification: lowest category (y/n)	−0.07	0.02
	(0.10)	(0.07)
Teacher qualification: highest category (y/n)	0.06	0.05
	(0.07)	(0.05)
Constant	0.41**	0.58**
	(0.12)	(0.10)
Observations	2626	1826
R-squared	0.04	0.02
Number of students	1313	913

Cluster-robust standard errors in parentheses:
* $p < 0.05$.
** $p < 0.01$.
Notes:
[a] "*high-achieving students*" refers to students who had a mark of 4 or 5 on both Russian language and mathematics in grade 10.
[b] "*low achieving students*" refers to students who had a mark of 2 or 3 on both Russian language and mathematics in grade 10.

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 results in Table 3 (Column 1), participating in college preparatory courses increases the performance of high-achieving students by 0.15 standard deviations. The estimate is statistically significant at the 5% level. By contrast, participating in college preparatory courses seems to have little or no impact on the performance of low-achieving students (−0.01 standard deviations—see Table 3, Column 2). The estimate is not statistically different from zero. Furthermore, private tutoring has no statistically significant impact on the performance of either high or low-achieving students (Table 3, Columns 1 and 2). Taken together, the results indicate that participating in college preparatory courses only benefit students from high-achieving backgrounds and that participating in private tutoring has no discernible benefit for high or low achieving students.

When we break the results down by region, we also find that shadow education favors high-achieving students (Appendix Table 1). College preparatory courses have a significant impact on the performance of high-achieving students in two regions: Krasnoyarsky krai (0.19 SDs, significant at the 5% level) and Pskovskaya oblast (0.22 SDs, significant at the 10% level). Private tutoring does not have any significant impacts on the performance of higher achieving students in these two regions. By contrast, private tutoring has a significant impact on the performance of high-achieving students in Yaroslavskaya oblast (0.19 SDs, significant at the 5% level).[5] As for lower achieving students, the results are consistent in all three regions. Neither college preparatory courses nor private tutoring has statistically significant effects on the performance of low-achieving students (Columns 2, 4, 6).

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. Toward this end, we apply the same cross-subject fixed effects model (as in Eq. (1)) and examine whether participating in shadow education impacts (a) whether (high and low-achieving) students prepare for the USE on their own or not (a dichotomous variable for Russian and math subjects separately); and (b) whether students always complete their homework or not (also a dichotomous variable for Russian and math subjects separately).

According to our estimates, we find little evidence that participating in shadow education (either college preparatory courses or private tutoring) causes students to substitute time away from their other out-of-school studies. The impact of participating in college preparatory courses on whether high-achieving students prepare for the USE on their own is slightly positive (0.06) but not statistically different from zero (Table 4, Column 1). The impact of participating in private tutoring on whether high-achieving students prepare for the USE on their own

[5] Although we lack data to explore why different types of shadow education are effective for high-achieving students in different regions, it is interesting to note that Yaroslavskaya oblast has much higher levels of spending per student (73,585 rubles in 2010) than Pskovskaya (57,325 rubles) and Krasnoyarskykrai (53,390 rubles) and also has higher mean USE scores in both Russian language and math.

Table 4
The impact of shadow education on whether students prepare for the college entrance exam (USE) on their own—for high and low achieving students (cross-subject student fixed effects model).

	High-achieving students[a] (1)	Low-achieving students[b] (2)
College preparatory course (y/n)	0.06	−0.03
	(0.03)	(0.04)
Private tutoring (y/n)	−0.01	−0.04
	(0.02)	(0.03)
Took additional classes in school (y/n)	0.05	0.10**
	(0.03)	(0.03)
Advanced subject study (y/n)	0.02	−0.00
	(0.01)	(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)	0.00	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	−0.02
	(0.02)	(0.03)
Teacher qualification: highest category (y/n)	−0.01	−0.01
	(0.02)	(0.02)
Constant	0.80**	0.70**
	(0.04)	(0.04)
Observations	2626	1826
R-squared	0.01	0.03
Number of students	1313	913

Cluster-robust standard errors in parentheses:
** $p < 0.01$.
Notes:
[a] "*high-achieving students*" refers to students who had a mark of 4 or 5 on both Russian language and mathematics in grade 10.
[b] "*low-achieving students*" 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 complete their homework—for high and low achieving students (cross-subject student fixed effects model).

	High-achieving students[a] (1)	Low-achieving students[b] (2)
College preparatory course (y/n)	0.00	−0.02
	(0.03)	(0.04)
Private tutoring (y/n)	0.00	−0.03
	(0.03)	(0.02)
Took additional classes in school (y/n)	0.13**	0.07
	(0.04)	(0.04)
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)	−0.01	0.08
	(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)
Constant	0.34**	0.14**
	(0.06)	(0.05)
Observations	2626	1826
R-squared	0.04	0.03
Number of students	1313	913

Cluster-robust standard errors in parentheses:
* $p < 0.05$.
** $p < 0.01$.
Notes:
[a] " *high-achieving students*" refers to students who had a mark of 4 or 5 on both Russian language and mathematics in grade 10.
[b] " *low-achieving students*" refers to students who had a mark of 2 or 3 on both Russian language and mathematics in grade 10.

is also not statistically different from zero. Although it appears that low-achieving students may be slightly less likely to prepare for the USE on their own if they participate in college preparatory courses or private tutoring, the impact estimates have small magnitudes (−0.04 and −0.03) and are not statistically different from zero (Table 4, Column 2).

Similarly, we find no impacts of participating in shadow education (either college preparatory courses or private tutoring) on students completing their homework. In particular, the impacts of participating in college preparatory courses or private tutoring on the likelihood of whether high-achieving students always complete their homework are 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 college preparatory courses or private tutoring (impact estimates of −0.02 and −0.03, both of which are 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.

4. Conclusion

Understanding the causal impacts of shadow education on student achievement is a policy-relevant topic in the field of education with major economic and social implications (Baker et al., 2001). Depending on its causal effects, shadow education may have a major role in explaining how individuals and nations build human capital (Baker et al., 2001). Understanding the (causal) costs and benefits of shadow education can further have major implications for how parents and students decide to divert resources among different consumption and investment activities and how educators decide to dedicate resources between formal and in-formal schooling (Jayachandran, 2014). If shadow education differentially benefits some social class students more than others, it can also have major implications for social and economic inequality (Buchmann et al., 2010; Stevenson and Baker, 1992).

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 performance, few large-scale studies have adequately addressed threats arising from selection bias (Dang and Halsey Rogers, 2008). In this study, our goal was to analyze the causal impact of shadow education on high school students' performance on college entrance exams. To fulfill this goal, we analyzed data from high school students in Russia 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 a variety of cross-subject (baseline) student, class, and teacher level 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 performance of low-achieving students and that only participation in one type of shadow education (college preparatory courses) has a positive impact on the performance 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 shadow education only benefits high-achieving students (that are also from higher socioeconomic backgrounds—see Table 1), it leads to greater educational inequality.

Our finding that low-achieving high school students in Russia receive no benefit from shadow education accords with the findings of studies from the United States (Buchmann et al., 2010; Domingue and Briggs, 2009) and may be a particular cause of concern for policymakers from post-socialist countries. As noted by Silova (2010), the rise of shadow education in post-socialist countries creates a tension between socialist legacies, which espouse free, public education, and global forces, which support market-drive, private education. If shadow education only helps high-achieving but not low-achieving students compete to enter college, policymakers may be especially concerned about the detrimental effects of shadow education on long-term social inequality.

We also posited two reasons why low-achieving students invest but fail to benefit from shadow education: (a) they have difficulty identifying high-quality shadow education; and/or (b) they substitute time away from their other out-of-school studies to participate in shadow education. While we cannot test the first possibility, our results suggest that participating in shadow education does not cause 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. Although we certainly cannot rule out other explanations, our findings tentatively suggest (and yet in no way prove) that low-achieving students may lack information about the quality of the shadow education programs they attend.

According to our findings, a first order concern that policymakers may wish to address is the potentially detrimental impacts of shadow education on social inequality and social welfare. Shadow education causes low-achieving students (that, on average, come from lower socioeconomic backgrounds) to fall further behind high-achieving students. Low-achieving students further experience a net economic loss by investing resources in shadow education. As our findings suggest that these social inequality and social welfare concerns are the result of low-achieving students mistakenly choosing to invest in low-quality programs, policymakers may wish to take a greater role in identifying and publishing information about the potential costs and benefits associated with different shadow education programs (Silova et al., 2006). Although identifying the causal impacts of the wide array of shadow education programs may prove difficult for policymakers in developing countries (Bray and Kwo, 2014), policymakers may wish to collect and publicize more basic information on shadow education programs that are correlated with costs and benefits (such as tutor qualifications, curricula and instructional media used, and tutoring fees). Policymakers can also issue general warnings about the importance of differentiating between higher and lower quality programs or even establish minimum standards for programs (Bray, 2011; Silova et al., 2006).

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Appendix A

Table A1
The impact of shadow education on the performance of high and low achieving students, by region (cross-subject student fixed effects model).

	Krasnoyarsky krai		Pskovskaya oblast		Yaroslavskaya oblast	
	High-achieving students[a]	Low-achieving students[b]	High-achieving students[a]	Low-achieving students[b]	High-achieving students[a]	Low-achieving students[b]
	(1)	(2)	(3)	(4)	(5)	(6)
College preparatory course (y/n)	0.19**	−0.16	0.22*	0.03	−0.00	0.09
	(0.08)	(0.11)	(0.13)	(0.17)	(0.09)	(0.08)
Private tutoring (y/n)	−0.04	0.08	0.13	0.01	0.19**	0.01
	(0.05)	(0.11)	(0.12)	(0.10)	(0.08)	(0.09)
Took additional classes in school (y/n)	0.01	−0.02	0.15	0.04	−0.15**	0.04
	(0.10)	(0.08)	(0.11)	(0.18)	(0.07)	(0.12)
Advanced subject study (y/n)	0.07	0.03	0.14	0.09	0.35***	0.26
	(0.13)	(0.10)	(0.09)	(0.12)	(0.11)	(0.16)
Class' grade 10 marks (4 or 5 = yes, 2 or 3 = no)	−0.33	−0.82***	−0.38	0.13	−0.03	−0.35
	(0.33)	(0.27)	(0.39)	(0.57)	(0.27)	(0.43)
Teacher experience: ≤10 years (y/n)	−0.17	−0.22*	−0.13	0.26	0.31**	0.09
	(0.14)	(0.12)	(0.20)	(0.26)	(0.12)	(0.18)
Teacher experience: 21–30 years (y/n)	0.15	−0.07	−0.21*	−0.12	0.17*	−0.11
	(0.15)	(0.10)	(0.11)	(0.16)	(0.10)	(0.12)
Teacher experience: >31 years (y/n)	−0.03	−0.05	−0.12	−0.02	−0.01	−0.18
	(0.20)	(0.12)	(0.11)	(0.20)	(0.13)	(0.12)
Teacher qualification: lowest category (y/n)	−0.15	0.21*	−0.41**	−0.14	0.17	−0.03
	(0.17)	(0.11)	(0.18)	(0.19)	(0.11)	(0.11)
Teacher qualification: highest category (y/n)	0.13	−0.00	−0.01	0.04	0.06	0.15*
	(0.12)	(0.10)	(0.12)	(0.13)	(0.07)	(0.08)
Constant	0.48**	−0.53***	0.47*	−0.85***	0.55***	−0.41**
	(0.20)	(0.13)	(0.24)	(0.26)	(0.14)	(0.16)
Observations	1018	770	706	472	902	584
R-squared	0.07	0.05	0.09	0.04	0.15	0.09

Table A1 (*Continued*)

	Krasnoyarsky krai		Pskovskaya oblast		Yaroslavskaya oblast	
	High-achieving students[a]	Low-achieving students[b]	High-achieving students[a]	Low-achieving students[b]	High-achieving students[a]	Low-achieving students[b]
	(1)	(2)	(3)	(4)	(5)	(6)
Number of students	509	385	353	236	451	292

Cluster-robust standard errors in parentheses:
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.
Notes:
[a] "High-achieving students" refers to students who had a mark of 4 or 5 on both Russian language and mathematics in grade 10.
[b] "Low-achieving students" refers to students who had a mark of 2 or 3 on both Russian language and mathematics in grade 10.

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