The Korean Economic Review
Volume 37, Number 2, Summer 2021, 287-326.
DOI : 10.22841/kerdoi.2021.37.2.004

Private Tutoring and Distribution of Student Academic Outcomes: An Implication of the Presence of Private Tutoring for Educational Inequality*

Changhui Kang** · Yoonsoo Park***

As private tutoring becomes globally widespread, many worry that an expansion of private tutoring aggravates educational inequality and ultimately intergenerational mobility. We address the issues by estimating the average and distributional effects of private tutoring on academic outcomes of Korean middle school students. Applying a semiparametric model recovering distributions in difference-in-differences models, we discover that the presence of private tutoring shifts the upper half of the outcome distribution rightward, but it exerts statistically insignificant effects on the lower half of the distribution. Our result suggests that the expansion of private tutoring in an education system is expected to aggravate educational inequality more than an empirical method reporting modest average effects suggests.

JEL Classification: I24, C21
Keywords: Private Tutoring, Academic Outcome, Educational Inequality, Quantile Treatment Effect

I. Introduction

Private tutoring — tutoring in academic subjects provided by individual tutors or tutoring institutions for financial gains (Bray and Kwok, 2003) — was once a

Received: March 2, 2020. Revised: Nov. 26, 2020. Accepted: Feb. 19, 2021.

* This paper is based on the third chapter of Park (2013).

** First Author, Professor, Department of Economics, Chung-Ang University, Republic of Korea, Email: ckang@cau.ac.kr. Kang gratefully acknowledges financial support from the Ministry of Education of the Republic of Korea and the National Research Foundation of Korea [Grant Number NRF-2016S1A3A2924944].

*** Corresponding Author, Assistant Professor, Department of Economics, Sookmyung Women's University, Republic of Korea, Email: yoonpark@sm.ac.kr. This research was supported by Sookmyung Women's University Research Grant (1-2003-2014).

phenomenon uniquely found in East Asian countries and in some developing countries with an ill-functioning public education system. It is now becoming a global phenomenon as competition to better colleges gets fierce in many parts of the world (Buchmann et al., 2010; Silova, 2010; Bray et al., 2013; Loyalka and Zakharov, 2016). The global private tutoring market was valued at approximately 96,218 million USD in 2017 and is expected to generate around 177,621 million USD by 2026 (Europe Industry News, 2019).

As private tutoring becomes widespread in an education system, many worry that such an expansion aggravates educational inequality and ultimately intergenerational mobility. To the extent that high-income parents spend more on private tutoring outside of formal education system, existing educational inequality is likely to exacerbate in the next generation and socio-economic inequality in general.

Theoretically, however, these concerns depend on whether and how much private tutoring raises a student's academic outcomes. If private tutoring improves academic outcomes of students that may affect their future labor market outcomes and socio-economic status, private tutoring may limit intergenerational mobility. By contrast, if private tutoring is not effective for improving academic outcomes and even crowd out the internal motivation of a student to self-study, existing concerns can be viewed overstated.

Despite its potential importance, not much is known about whether and to what extent private tutoring affects the academic outcomes of students. Few studies attempt to measure the effectiveness of private tutoring for student outcomes. The results are fairly mixed though. Some studies (Stevenson and Baker, 1992; Tansel and Bircan, 2005; Ha and Harphan, 2005; Dang, 2007; Ono, 2007; Loyalka and Zakharov, 2016) report strong positive effects, whereas others (Briggs, 2001; Kang, 2007; Gurun and Millimet, 2008; Ryu and Kang, 2013) present that the effects are close to zero or even negative (Lee et al., 2004; Cheo and Quah, 2005).

The literature is also limited in that studies mainly focus on estimating *average* effects of private tutoring, assuming that the effects are homogeneous. This study aims to contribute to the literature by examining *distributional* (as well as average) effects of private tutoring on academic outcomes of students, allowing the heterogeneous effects on different students along the performance distribution.

As in the case of the average causal effects of private tutoring, the primary difficulty in estimating the distributional effects of private tutoring is endogeneity of the receipt of private tutoring. To deal with such an endogeneity, we rely on an empirical model developed by Bonhomme and Sauder (2011), which controls for potential differences in observable (e.g., student, family, and school backgrounds) and time-invariant unobservable (e.g., cognitive ability) educational inputs of students that may affect test score outcomes and private tutoring decisions. A unique advantage of using this model is that it allows us to estimate the average and distributional effects using panel data on test scores and panel fixed-effects.

We apply Bonhomme and Sauder's (2011) methods to the longitudinal data on nationally representative middle school students in South Korea from 2005 to 2007. South Korea offers an interesting case for studying the average and distributional effects of private tutoring in that it has a well-developed private tutoring market. We find that the effects of private tutoring tend to be positive on the upper half of the outcome distribution but statistically insignificant on the lower half of the distribution. However, the detailed shape of the distributional effects vary by subject. The results suggest that private tutoring widens the outcome gap across students by mainly improving academic outcomes of high-achieving students. Considering that academic outcomes of students are closely related to their future earnings and socio-economic status, our findings also suggest that the expansion of private tutoring in an education system is expected to aggravate future socio-economic inequality more than studies measuring simple average effects suggest.

The remainder of the paper proceeds as follows. Previous studies are summarized in section II. Data are explained in section III. Statistical methods and empirical findings are presented in section IV. The paper concludes in section V.

II. Previous Literature

Some studies examine the effects of private tutoring on students' academic performance. Stevenson and Baker (1992), Tansel and Bircan (2005), Ha and Harphan (2005), and Ono (2007) examine data from Japan, Turkey, Vietnam, and Japan, respectively, reporting strong positive effects of private tutoring. On the contrary, Briggs (2001) finds a negligible effect in the U.S., whereas Lee et al. (2004) and Choe and Quah (2005) report even negative effects of private tutoring in Korea and Singapore, respectively. However, these studies do not explicitly deal with potential endogeneity of private tutoring assuming selection on observables, so their results should be interpreted with caution.

Allowing for selection on unobservables, recent studies attempt to address the potential endogeneity of private tutoring in various ways. Dang (2007) examines the effect of private tutoring expenditures on the self-reported academic performance of students using nationally representative household survey data in Vietnam during 1997–1998. To address the endogeneity of private tutoring expenditures, Dang (2007) estimates a simultaneous equation system consisting of a Tobit model for private tutoring expenditures and an ordered probit model for the self-reported academic performance. Dang (2007) finds that private tutoring has a positive effect on students' academic performance.

Dang (2007) deals with the endogeneity of private tutoring by explicitly modeling the process generating private tutoring expenditures and academic performance of the student using a simultaneous framework. By contrast, Kang (2007) tries to find an exogenous variation that affects the private tutoring decisions of parents but not the academic outcomes of the student. In particular, Kang (2007) uses a student's birth order as an instrumental variable (IV) for private tutoring expenditures. The logic is that parents tend to have more concerns about a first-born child's education and invest more for the student's private tutoring than for the later-borns. The problem is that a student's birth order is determined exogenously by nature and is unlikely to directly affect the academic performance of the student. Using the first-born indicator as an IV for tutoring expenditures, Kang (2007) finds a modest positive effect of private tutoring on the national college entrance exam scores for high school graduates in Korea: a 10 percent increase in tutoring expenditures improves only approximately 0.56 percentile point in the test score.

Although the IV used by Kang (2007) is fairly strong, reasonable doubts arise about the validity of the exclusion restriction. If parents indeed are more concerned about their first-born child's education and invest more for the first-born's private tutoring, then other parental inputs (e.g., helping children with their homework) will be also greater for the first-born than for the later-borns. To the extent that these parental inputs are related with the academic outcomes of the student, the validity of the IV strategy becomes questionable. Gurun and Millimet (2008) point out this issue and take a different approach. As a valid exclusion restriction is unavailable in their data, Gurun and Millimet (2008) try to assess the importance of the potential endogeneity of private tutoring by using the bivariate probit framework suggested by Altonji et al. (2005, 2008). They discover that the estimated effect of private tutoring becomes statistically insignificant and even falls below zero when only a moderate level of endogeneity is allowed. Given these results, they conclude that the strong positive effects of private tutoring often reported in previous studies may have been driven by the potential endogeneity problem.

Recently, Ryu and Kang (2013) extend Kang's (2007) study by employing alternative empirical strategies. Specifically, they employ the monotone instrumental variable (MIV) strategy by Manski and Pepper (2000) and try to estimate the *bounds* of the causal effect of private tutoring on test scores. In the standard IV strategy, an IV is not allowed to affect an outcome variable directly (i.e., exclusion restriction). By contrast, in the MIV strategy by Manski and Pepper (2000), an MIV may affect an outcome variable directly but only *monotonically* (i.e., either positively or negatively). Using a child's first-born status as an MIV for private tutoring expenditures, Ryu and Kang (2013) find that the estimated upper bound for the causal effect of private tutoring expenditures is small, which implies the causal effect is likely to be close to zero.[1]

[1] A child's first-born status, which is used as an IV in Kang (2007), may not be a valid IV for private tutoring expenditures because the first-born may receive a larger parental support than the later-borns

Most of the previous studies employ cross-section data and apply relevant statistical methods to control for endogeneity. To the contrary, Ryu and Kang (2013) and Loyalka and Zakharov (2016) exploit the merits of panel data and apply panel fixed-effects methods for estimation. Ryu and Kang (2013) find statistically insignificant effects of private tutoring in South Korea. Loyalka and Zakharov (2016) reports insignificant effects on low-achieving students and significantly positive effects of college preparatory courses (a form of paid private tutoring) on low-achieving students in Russia.

Although previous studies that estimate average causal effects of private tutoring offer implications for educational inequality, directly measuring the effects of private tutoring on the distribution of student academic outcomes and educational inequality is warranted. All existing studies on private tutoring examine average effects. Some studies examine distributional effects of formal school inputs though (Eide et al., 2002; Bedard, 2003; Maasoumi et al., 2005; Lamarche, 2008; Corak and Lauzon, 2009). To the best of our knowledge, this research is the first to explicitly examine the distributional effects of private tutoring on student academic outcomes.

Studies examining the effectiveness of educational investments in formal schooling sectors often exploit experimental (e.g., the STAR experiment in Krueger and Whitmore, 2001) and/or quasi-experimental (e.g., private school voucher programs in McEwan, 2004) designs (see also Sadoff, 2014). By contrast, studies on private tutoring tend not to enjoy the merits of such an exogenous variation. Similarly, we do not find a plausible source of exogenous cross-sectional variation in students' (or their parents') private tutoring decisions from our data. Considering this limitation, we attempt to estimate the average and distributional effects of private tutoring by relying on the longitudinal nature of the data, which will be described in section IV.

in many other forms besides private tutoring. However, the first-born indicator can still be used as an MIV of Manski and Pepper (2000) as long as a child's birth order is monotonically related with the student's academic performance. The empirical strategy of Ryu and Kang (2013) is more advanced than that of Kang (2007) in that it draws the same conclusion while relaxing a restrictive IV assumption to a less restrictive MIV assumption. To derive the sharp bounds, Ryu and Kang (2013) employ two additional monotonicity assumptions: (1) the effect of private tutoring expenditures on test scores is non-negative for all students (monotone treatment response: MTR) and (2) the non-random selection into a larger amount of private tutoring expenditures is positive on average (monotone treatment selection: MTS). Seeing that some studies report evidence of negative effects of private tutoring (Lee et al., 2004; Choe and Quah, 2005) and negative selection into a larger amount of private tutoring expenditures (Gurun and Millimet, 2008), the MTS and MTR assumptions seem to be restrictive. The validity of the causal inference based on these assumptions will be limited.

III. Data

The data for this study are from the Korea Education Longitudinal Study (KELS). The KELS is an annual longitudinal survey whose basic structure is similar to that of the National Educational Longitudinal Studies of the U.S. (Ryu and Kang, 2013). A nationally representative sample of 6,908 seventh graders (age 13) was first surveyed in 2005 and followed every year since then.[2]

Every year, the KELS conducts standardized academic achievement tests in three subjects — Korean, English, and math — to measure students' understanding of the contents of the national curriculum for each subject. We use the KELS test scores of the three academic subjects, which take a value between 0 and 100[3], as outcome variables for the analysis in section IV. Among the three-year test scores, we mainly use the scores from the second and third waves (2006 and 2007) for the analysis in section IV.B and the scores from the first wave (2005) for the falsification test in section IV.C.[4]

The KELS also surveyed parents, teachers, and school principals of each of the 6,908 students to collect information on the family and school characteristics of the students. We use the information on private tutoring experience responded by the parents to define the treatment variable for our analysis. Specifically, we divide students into two groups — treatment and control groups — on the basis of whether they received private tutoring in 2007 (treatment group) or not (control group).

[2] In the Korean educational system, seventh grade is the first year of middle school.

[3] Concerned that every student's test score may simultaneously rise as all of them take private tutoring but that an empirical analysis based on scores normalized by the mean and standard deviation fails to capture a positive effect of private tutoring, we rely on raw test scores that take a value between 0 and 100. If normalized test scores are used instead of raw scores, the primary results of this paper are not affected. They are available upon request.

[4] Another reason we mainly use the 2006–2007 data for our analysis is that the reference period of the questions on private tutoring investment changed between the first wave (2005) and the other two waves (2006 and 2007). In 2005, the KELS asked a student's private tutoring experience during the survey month (October 2005). In 2006 and 2007, it asked a student's private tutoring experience during the entire survey year. Pupils may receive different amounts of tutoring in different seasons (Bray and Kwok, 2003), so we choose to focus on the second and third waves of the KELS during which the survey collected the information on private tutoring in a consistent manner.

[Table 1] Summary Statistics (Korean)

	Total		Treatment		Control	
	Mean (1)	S.D. (2)	Mean (3)	S.D. (4)	Mean (5)	S.D. (6)
Treatment (in 2007)						
Private tutoring (yes=1)	.570	.495	1.00	0.00	0.00	0.00
Outcome (in 2007)						
Test scores	57.9	20.6	58.7	20.2	57.0	21.0
Baseline characteristics (in 2006)						
Student characteristics						
Test scores	60.1	18.7	60.8	18.6	59.3	18.8
Private tutoring (yes=1)	.542	.498	.727	.445	.296	.456
Female (yes=1)	.482	.500	.430	.495	.550	.498
First born (yes=1)	.499	.500	.528	.499	.461	.499
Number of siblings	1.21	.724	1.18	.679	1.26	.777
Disabled (yes=1)	.019	.138	.019	.136	.020	.140
Parental characteristics						
Average age	42.3	4.07	42.1	3.66	42.6	4.55
Average years of education	12.8	2.22	13.0	2.10	12.6	2.35
Married (yes=1)	.896	.305	.931	.253	.850	.357
Monthly income (1000 KRW)	3378	2394	3642	2461	3027	2256
Having a religion (yes=1)	.685	.464	.698	.459	.670	.471
School characteristics						
Large city (yes=1)	.465	.499	.474	.499	.453	.498
Medium city (yes=1)	.447	.497	.458	.498	.433	.496
Rural area (yes=1)	.088	.284	.068	.252	.115	.319
Private school (yes=1)	.205	.404	.199	.399	.213	.409
Coed school (yes=1)	.640	.480	.643	.479	.637	.481
Boy-only school (yes=1)	.188	.390	.204	.403	.166	.372
Girl-only school (yes=1)	.172	.378	.153	.360	.197	.398
Grade size (# of students)	299	149	313	142	280	155
Class size (# of students)	35.4	5.47	35.8	5.01	35.0	5.99
Number of observations	4073		2321		1752	

[Table 2] Summary Statistics (English)

	Total		Treatment		Control	
	Mean (1)	S.D. (2)	Mean (3)	S.D. (4)	Mean (5)	S.D. (6)
Treatment (in 2007)						
Private tutoring (yes=1)	.756	.429	1.00	0.00	0.00	0.00
Outcome (in 2007)						
Test scores	56.0	26.5	60.4	26.1	42.4	23.0
Baseline characteristics (in 2006)						
Student characteristics						
Test scores	57.1	24.1	60.9	23.8	45.2	20.9
Private tutoring (yes=1)	.746	.435	.869	.338	.365	.482
Female (yes=1)	.489	.500	.478	.500	.523	.500
First born (yes=1)	.504	.500	.532	.499	.417	.493
Number of siblings	1.20	.706	1.17	.652	1.31	.843
Disabled (yes=1)	.019	.135	.018	.132	.021	.144
Parental characteristics						
Average age	42.3	3.99	42.1	3.65	42.7	4.88
Average years of education	12.9	2.21	13.2	2.13	12.0	2.21
Married (yes=1)	.903	.297	.937	.243	.796	.403
Monthly income (1000 KRW)	3427	2320	3727	2363	2494	1900
Having a religion (yes=1)	.689	.463	.699	.459	.657	.475
School characteristics						
Large city (yes=1)	.469	.499	.491	.500	.401	.490
Medium city (yes=1)	.447	.497	.440	.496	.468	.499
Rural area (yes=1)	.084	.278	.069	.254	.131	.337
Private school (yes=1)	.200	.400	.200	.400	.201	.401
Coed school (yes=1)	.641	.480	.648	.478	.620	.486
Boy-only school (yes=1)	.186	.389	.186	.389	.188	.391
Girl-only school (yes=1)	.173	.378	.167	.373	.192	.394
Grade size (# of students)	304	149	318	144	261	158
Class size (# of students)	35.6	5.42	36.0	4.98	34.2	6.42
Number of observations	4464		3377		1087	

[Table 3] Summary Statistics (Math)

	Total		Treatment		Control	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment (in 2007)						
Private tutoring (yes=1)	.761	.426	1.00	0.00	0.00	0.00
Outcome (in 2007)						
Test scores	52.9	26.0	57.3	25.7	38.9	22.0
Baseline characteristics (in 2006)						
Student characteristics						
Test scores	52.6	24.3	56.2	24.2	41.1	20.9
Private tutoring (yes=1)	.743	.437	.861	.346	.368	.483
Female (yes=1)	.493	.500	.484	.500	.521	.500
First born (yes=1)	.507	.500	.532	.499	.427	.495
Number of siblings	1.20	.699	1.16	.643	1.31	.844
Disabled (yes=1)	.020	.139	.019	.136	.022	.147
Parental characteristics						
Average age	42.3	3.98	42.1	3.60	42.7	4.97
Average years of education	12.9	2.22	13.2	2.13	12.0	2.26
Married (yes=1)	.903	.295	.936	.245	.799	.401
Monthly income (1000 KRW)	3458	2314	3767	2359	2473	1851
Having a religion (yes=1)	.694	.461	.705	.456	.657	.475
School characteristics						
Large city (yes=1)	.468	.499	.492	.500	.390	.488
Medium city (yes=1)	.446	.497	.442	.497	.460	.499
Rural area (yes=1)	.086	.280	.065	.247	.150	.357
Private school (yes=1)	.201	.401	.200	.400	.202	.402
Coed school (yes=1)	.639	.480	.646	.478	.614	.487
Boy-only school (yes=1)	.186	.389	.186	.389	.187	.390
Girl-only school (yes=1)	.175	.380	.167	.373	.200	.400
Grade size (# of students)	305	149	320	143	255	158
Class size (# of students)	35.6	5.43	36.1	4.97	34.0	6.45
Number of observations	4574		3482		1092	

Tables 1, 2, and 3 show the summary statistics of our Korean, English, and math samples, respectively. After removing observations with missing information on the variables we use in this study, we have 4,073, 4,464, and 4,574 valid observations for the Korean, English, and math samples, respectively.[5] In each of the three tables, columns (1) to (6) show summary statistics of the entire sample, treatment group, and control group, respectively. In all three subjects, students in the treatment group tend to report better academic performance than those in the control group. In the Korean achievement test, students who receive private tutoring score slightly higher on average than those who do not receive private tutoring by approximately 1.7 points. This is nearly 8 percent of the standard deviation of Korean test scores of the treatment group. By contrast, students in the treatment group achieve on average 18.0 and 18.4 points higher in the English and math tests than those not receiving private tutoring, which amount to roughly 69 percent and 72 percent of the standard deviation of the treatment group, respectively. The tables also show that, even before the treatment is realized, students in the treatment group tend to score higher in the achievement tests and are more likely to receive private tutoring than those in the control group. The two groups also present a large difference in their student, parental, and school characteristics. To compare the test scores of students in the treatment and control groups at a common baseline, we control for test scores and private tutoring status of the students as well as their individual, parental, and school characteristics that are observed in 2006 throughout the analysis in section IV.

IV. Empirical Analysis

1. Average Effects of Private Tutoring

For each of the Korean, English, and math samples, we have data on

$$Y_{i1}, Y_{i2}, D_i, X_i \tag{1}$$

where Y_{i1} and Y_{i2} denote test scores of student i in 2006 (denoted by period 1 hereafter) and 2007 (denoted by period 2 hereafter), respectively; D_i is our treatment indicator that takes 1 if student i receives private tutoring in period 2 and 0 otherwise; and X_i is a vector of the individual, parental, and school

[5] In addition to the observations that have missing information on key variables, we remove students whose subject scores between 2006 and 2007 tests are more than 50 points apart because they seem to have neglected one of the tests. The number of these students is 53, 153, and 123 for the Korean, English, and math samples, respectively. Although the empirical results of this study are drawn without them, the primary findings are not altered qualitatively if we include them in the analysis samples. The results are available upon request.

characteristics of student i.

The observed test score of student i in period 2 (Y_{i2}) can be written as

$$Y_{i2} = D_i Y_{i2}^1 + (1 - D_i) Y_{i2}^0 \tag{2}$$

where Y_{i2}^1 (or Y_{i2}^0) denotes the potential test score of student i in period 2 had they received (or not received, respectively) private tutoring during that period.

In this section, we try to identify the average treatment effect on the treated (ATT).

$$ATT = E[Y_{i2}^1 - Y_{i2}^0 \mid D_i = 1] \tag{3}$$
$$= E[Y_{i2} \mid D_i = 1] - E[Y_{i2}^0 \mid D_i = 1] \tag{4}$$

In Equation (4), $E[Y_{i2} \mid D_i = 1]$ is empirically observable, but $E[Y_{i2}^0 \mid D_i = 1]$ is counterfactual and unobservable. To identify $E[Y_{i2}^0 \mid D_i = 1]$, we employ a semiparametric estimation model developed by Bonhomme and Sauder (2011).[6] Specifically, we model the potential post-treatment test score of student i in the state where they do not receive private tutoring (Y_{i2}^0) and the baseline test score of student $i(Y_{i1})$ as the sum of three components:

$$Y_{i1} = f_1(X_i) + \eta_i + v_{i1} \tag{5}$$
$$Y_{i2}^0 = f_2^0(X_i) + \eta_i + v_{i2}^0, \tag{6}$$

where X_i denotes the student, parental, and school characteristics of student i whose effects on test scores are flexibly modeled as arbitrary functions of $f_1(\cdot)$ and $f_2^0(\cdot)$; η_i represents unobservable characteristics of student i that are fixed between the two periods (e.g., cognitive ability); and v_{i1} and v_{i2}^0 represent time-varying unobservable shocks to test scores (e.g., physical conditions on the exam day) that are allowed to be correlated with one another in an unrestricted way. Equations (5) and (6) may be viewed as an educational production function (Hanushek, 1986) that relates observable (X_i) and unobservable (η_i, v_{i1}, v_{i2}^0) educational inputs to test score outputs (Y_{i1}, Y_{i2}^0) in each period. Except for its additive structure, the educational production function is fairly flexible in that it does not impose any distributional or functional-form restrictions on its three components.

To identify ATT, we impose the following assumption on the education production functions of Equations (5) and (6):

[6] Our illustration of the method is heavily drawn from sections II and III of Bonhomme and Sauder (2011).

Assumption 1: (v_{i1}, v_{i2}^0) are independent of D_i conditional on X_i

Assumption 1 requires no systematic difference in time-varying unobservables (v_{i1}, v_{i2}^0) of the test scores between the treatment and control groups conditional on observable characteristics (X_i), which is similar with the usual parallel-trend assumption of difference-in-differences model.[7]

Under Assumption 1, the ATT in Equation (3) or (4) can be identified as (Abadie, 2005; Bonhomme and Sauder, 2011)[8]

$$ATT = \frac{1}{\Pr[D_i = 1]} E\left[\left\{ \frac{D_i - \Pr[D_i = 1 \mid X_i]}{1 - \Pr[D_i = 1 \mid X_i]} \right\} (Y_{i2} - Y_{i1}) \right], \tag{7}$$

for which we need a usual common support assumption.

Assumption 2: $\Pr[D_i = 1] > 0$ and $\Pr[D_i = 1 \mid X_i] < 1$ with probability 1

We estimate the ATT of Equation (7) by

$$\widehat{ATT} = \frac{1}{\frac{1}{N}\sum_{i=1}^{N} D_i} \frac{1}{N} \sum_{i=1}^{N} \left[\frac{D_i - \widehat{\Pr}[D_i = 1 \mid X_i]}{1 - \widehat{\Pr}[D_i = 1 \mid X_i]} (Y_{i2} - Y_{i1}) \right] \tag{8}$$

where $\widehat{\Pr}[D_i = 1 \mid X_i]$ is estimated by a logit regression of D_i on X_i to avoid the curse of high dimensionality problem. We also restrict our estimation sample to observations with $.05 < \widehat{\Pr}[D_i = 1 \mid X_i] < .95$ to ensure that Assumption 2 will hold.[9] We compute the standard errors of $\widehat{ATT}$ by bootstrapping with 2,000 iterations.

Table 4 reports the estimation results for $\widehat{ATT}$ in Equation (8). For Korean, the estimated average effects are statistically insignificant regardless of the choice of covariate specifications. This result suggests that students on average do not benefit

[7] Assumption 1 can be viewed as a rather strong assumption in that it requires the treatment and control groups to have unobservable heterogeneity only in terms of time-invariant factors. This assumption rules out the possibility that unobservable student-specific temporal shocks to test scores may affect students' decisions whether or not to receive private tutoring. This should be kept in mind when interpreting the results of this study.

[8] Details on deriving Equation (7) are provided in Appendix A1.

[9] The proportions of the removed observations vary from 0% to 6% depending on the samples and specifications. These proportions are smaller than those in the empirical example of Bonhomme and Sauder (2011) where 10% of observations are removed. Note that due to the trimming procedure, our estimation results are only valid for students whose observable characteristics are not too extreme to find their counterparts with the same characteristics but the opposite treatment status in the estimation sample.

[Table 4] Average Effects of Private Tutoring

Dependent variable:	Specifications		
Test scores in 2007	(1)	(2)	(3)
A. Subject: Korean			
Estimated ATT	.511	.616	.579
(S.E.)	(.654)	(.657)	(.583)
Covariates:			
Student characteristics	Yes	Yes	Yes
Parental characteristics	No	Yes	Yes
School characteristics	No	No	Yes
Number of observations	4073	4073	4073
B. Subject: English			
Estimated ATT	2.58	1.96	2.00
(S.E.)	(.774)	(.863)	.863)
Covariates:			
Student characteristics	Yes	Yes	Yes
Parental characteristics	No	Yes	Yes
School characteristics	No	No	Yes
Number of observations	4464	4464	4464
C. Subject: Math			
Estimated ATT	4.22	4.41	4.64
(S.E.)	(.915)	(1.02)	(1.00)
Covariates:			
Student characteristics	Yes	Yes	Yes
Parental characteristics	No	Yes	Yes
School characteristics	No	No	Yes
Number of observations	4574	4574	4574

Note. The outcome variable is achievement test scores of students measured in November 2007. The treatment variable (private tutoring) is an indicator that takes 1 if a student has ever received private tutoring in 2007 and 0 otherwise. Covariates include (1) student characteristics: a dummy for having ever received private tutoring in 2006, a dummy for female, a dummy for being handicapped, number of siblings; (2) parental characteristics: parents' average age, parents' average years of education, a dummy for being married, parents' average monthly income, and a dummy for having a religion; and (3) school characteristics: a dummy for being located in a metropolitan area, a dummy for being located in a suburban area, a dummy for private school, a dummy for boy-only school, a dummy for girl-only school, logarithm of grade size, and class size. Standard errors are computed by bootstrap of 2000 iterations.

from receiving private tutoring for the subject. For English and math, when all the student, parental, and school characteristics are controlled for, we find average effects of 2.00 and 4.64 points, which are roughly 8 percent and 18 percent of the standard deviation of the test score, respectively. The magnitudes of the estimated effects generally agree with the findings of Kang (2007) and Ryu and Kang (2013).[10] Column (4) of Table A1 in the Appendix shows the parametric difference-in-differences estimation results for the average effects of the private tutoring, which is analogous to the results in column (3) of Table 4. The parametric results in Table A1 are more or less similar with the semiparametric results in Table 4.

2. Distributional Effects of Private Tutoring

The empirical model in section IV.1 evaluates the *average* effects of receiving private tutoring on test scores. We find that private tutoring improves test scores of students on average by approximately 2.00 and 4.64 points in English and math, respectively, but it exerts no effect in Korean. Although estimating the average effect of private tutoring offers information on how private tutoring affects academic outcomes of students, the estimates may miss important features of the effects of private tutoring. For example, private tutoring may help students who are left behind in their school classes more than those who are already in good standing for themselves, narrowing the existing outcome gap across students. It is possible that more advanced students can make better use of private tutoring to enhance their academic performance further, widening the existing outcome gap across students. To account for potential heterogeneity of the effects of private tutoring and uncover how the presence of private tutoring affects the entire distribution of student academic outcomes, we employ a method suggested by Bonhomme and Sauder (2011) and estimate the *distributional* effects of receiving private tutoring on test scores at each percentile point of a test score distribution.

[10] In our estimation sample, the average tutoring expenditures of the treatment group — or the difference in average tutoring expenditures between the treatment and control groups — are 218.8 and 226.5 (in 1,000 KRW) for English and math, respectively. Thus, the estimated effects in Table 4 imply that an increase in tutoring expenditures from zero (i.e., the average expenditure of the control groups) to 218.8 and 226.5 (i.e., the average expenditure of the treatment groups) leads to an increase in test score by 2.00 and 4.64 for English and math, respectively. Evaluated at the average test score of the treatment group for English (60.4) and math (57.4), such estimates are a 3.3-percent (=2.00/60.4) increase for English and an 8.1-percent (=4.64/57.4) increase for math. Therefore, we interpret that a 10-percent increase in tutoring expenditures raises the average test score of English and math by 0.33 and 0.81 percent, respectively. These amounts of the effect generally agree with the findings of Kang (2007) and Ryu and Kang (2013). Such magnitudes are, however, much smaller than the amount of improvement in the test score (2.8 percent to 3.6 percent) due to a 10-percent increase in public school expenditures in the U.S. summarized by Krueger (2003). Our estimates are more analogous to the effect sizes suggested by Guryan (2001) in terms of test scores (0.77 percent to 1.15 percent) and by Card and Krueger (1996) in terms of labor market earnings (0.7 percent to 1.1 percent).

The object of interest in this section is the quantile treatment effect on the treated (QTT) which is defined as

$$QTT(\tau) = F^{-1}_{Y_{i2}|D_i=1}(\tau) - F^{-1}_{Y^0_{i2}|D_i=1}(\tau), \quad \tau \in (0,1), \tag{9}$$

where $\tau \in (0,1)$ represents a percentile point of a test score distribution and $F^{-1}_W(\cdot)$ denotes the inverse of the cumulative distribution function (CDF) of a random variable W. Note that the distribution of $Y_{i2} \mid D_i = 1$ — post-treatment test scores of students who receive private tutoring — is empirically observable, and, hence, it is straightforward to estimate $F^{-1}_{Y_{i2}|D_i=1}(\cdot)$ nonparametrically. The key issue is how to estimate $F^{-1}_{Y^0_{i2}|D_i=1}(\cdot)$, which is counterfactual and thus unobservable.

Following Bonhomme and Sauder (2011), we maintain all the assumptions in section IV.1 and further assume that

Assumption 3: (v_{i1}, v^0_{i2}) are independent of η_i conditional on X_i and D_i.

Assumption 3 presumes that the temporal shocks to test scores (v_{i1} and v^0_{i2}) are independent of time-invariant unobservables (η_i) among students who share the same observable characteristics (X_i and D_i). For example, this assumption excludes the possibility that students with high levels of motivation and cognitive ability (represented by η_i) face systematically higher (or lower) patterns of physical conditions on their exam days (represented by v_{i1} and v^0_{i2}) conditional on their observable characteristics (X_i and D_i).

Under the educational production functions of Equations (5) and (6) and Assumption 1 to Assumption 3, Bonhomme and Sauder (2011) show that the probability density function (PDF) of $Y^0_{i2} \mid D_i = 1$ is identified as[11]

$$f_{Y^0_{i2}|D_i=1}(y) = \frac{1}{2\pi}\int_{-\infty}^{\infty} \exp(-jty) \frac{1}{\Pr[D_i = 1]} E[\omega(t \mid X_i)(1-D_i)\exp(jtY_{i2})]dt \tag{10}$$

where $j = \sqrt{-1}$, $t \in \mathbf{R}$, and

$$\omega(t \mid X_i) \equiv \frac{E[D_i \exp(jtY_{i1}) \mid X_i]}{E[(1-D_i)\exp(jtY_{i1}) \mid X_i]} \tag{11}$$

Following Bonhomme and Sauder (2011), we estimate the counterfactual density in Equation (10) with

[11] Details of the identification procedure are presented in Appendix A2.

$$\hat{f}_{Y_{i2}^0|D_i=1}(y) = \frac{1}{2\pi}\int_{-T_N}^{T_N} \exp(-jty)\frac{1}{\frac{1}{N}\sum_{i=1}^{N} D_i}\left(\frac{1}{N}\sum_{i=1}^{N}\hat{\omega}(t\,|\,X_i)(1-D_i)\exp(jtY_{i2})\right)dt \quad (12)$$

where $j=\sqrt{-1}$, $t\in\mathbf{R}$, and

$$\hat{\omega}(t\,|\,X_i) = \frac{\hat{E}[D_i\exp(jtY_{i1})\,|\,X_i]}{\hat{E}[(1-D_i)\exp(jtY_{i1})\,|\,X_i]} \quad (13)$$

Seeing that X_i consists of many covariates including continuous variables, we approximate the conditional expectations in the numerator and denominator of Equation (13) with linear projections of $D_i\exp(jtY_{i1})$ and $(1-D_i)\exp(jtY_{i1})$ onto X_i, respectively, to avoid the curse of dimensionality. We choose the trimming parameter T_N in Equation (12), which is analogous to choosing a bandwidth in nonparametric density estimation, by the rule of thumb method suggested by Diggle and Hall (1993).[12] We compute the integration using the trapezoid rule with 200 equidistant nods.

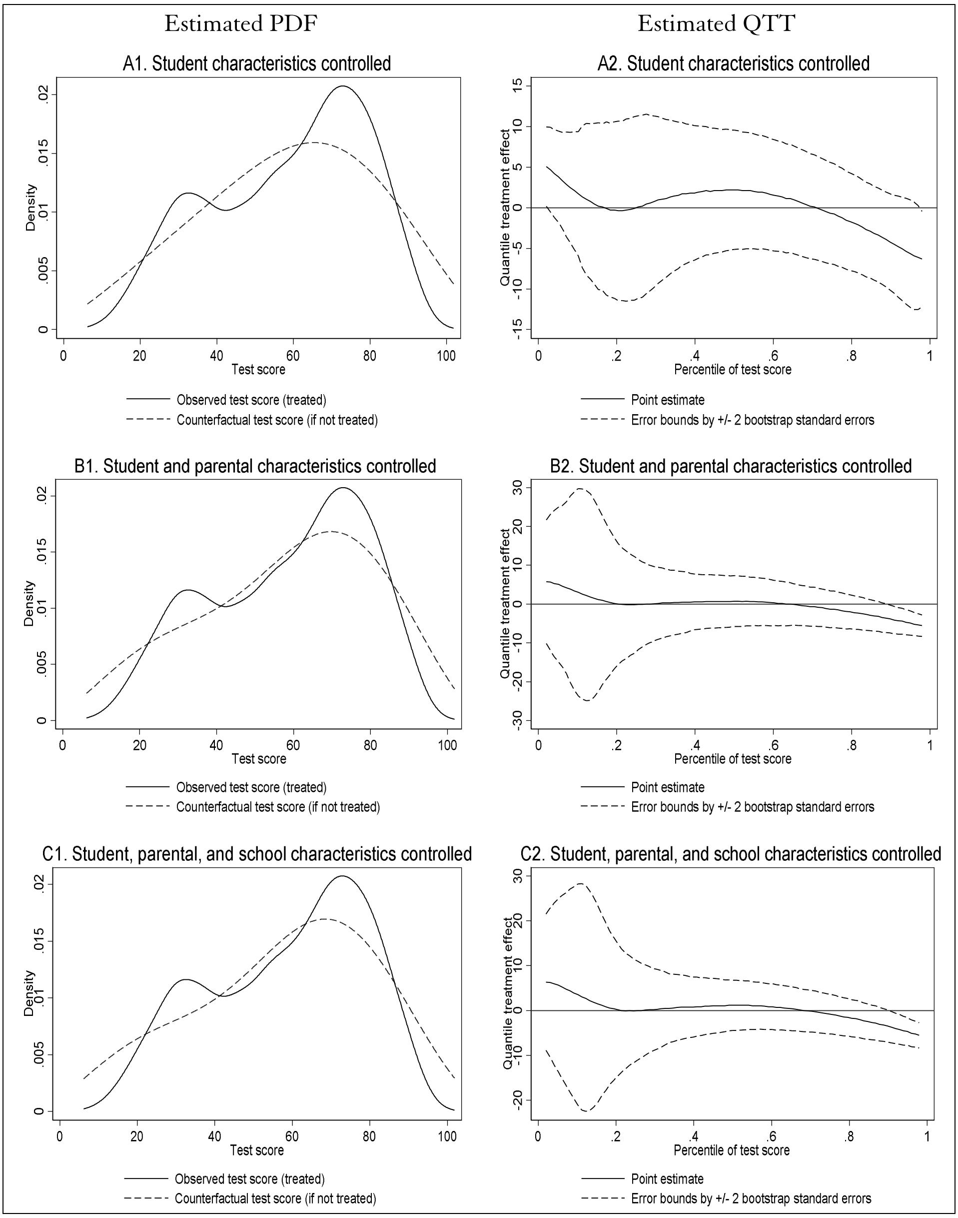
The estimation results of Equation (12) for each of the three subjects are presented in the left columns of Figures 1, 2, and 3. In each of the three figures, we report estimation results for three different covariate specifications. In plot A, we include only student characteristics in X_i of Equation (12), whereas in plots B and C, we augment parental and school characteristics to the list of covariates. In all of the plots, solid lines represent the kernel density estimates for the realized test score distribution of students who receive private tutoring ($Y_{i2}\,|\,D_i=1$).[13] Dashed lines represent the counterfactual test score distribution of students who receive private tutoring had they not received it ($Y_{i2}^0\,|\,D_i=1$). We compare a realized test score distribution of students receiving private tutoring with a counterfactual test score distribution of the same group of students, so any difference between the two distributions can be attributable to the causal effect of private tutoring.

---

[12] Details on how we determine the values of T_N are given in Appendix A3.

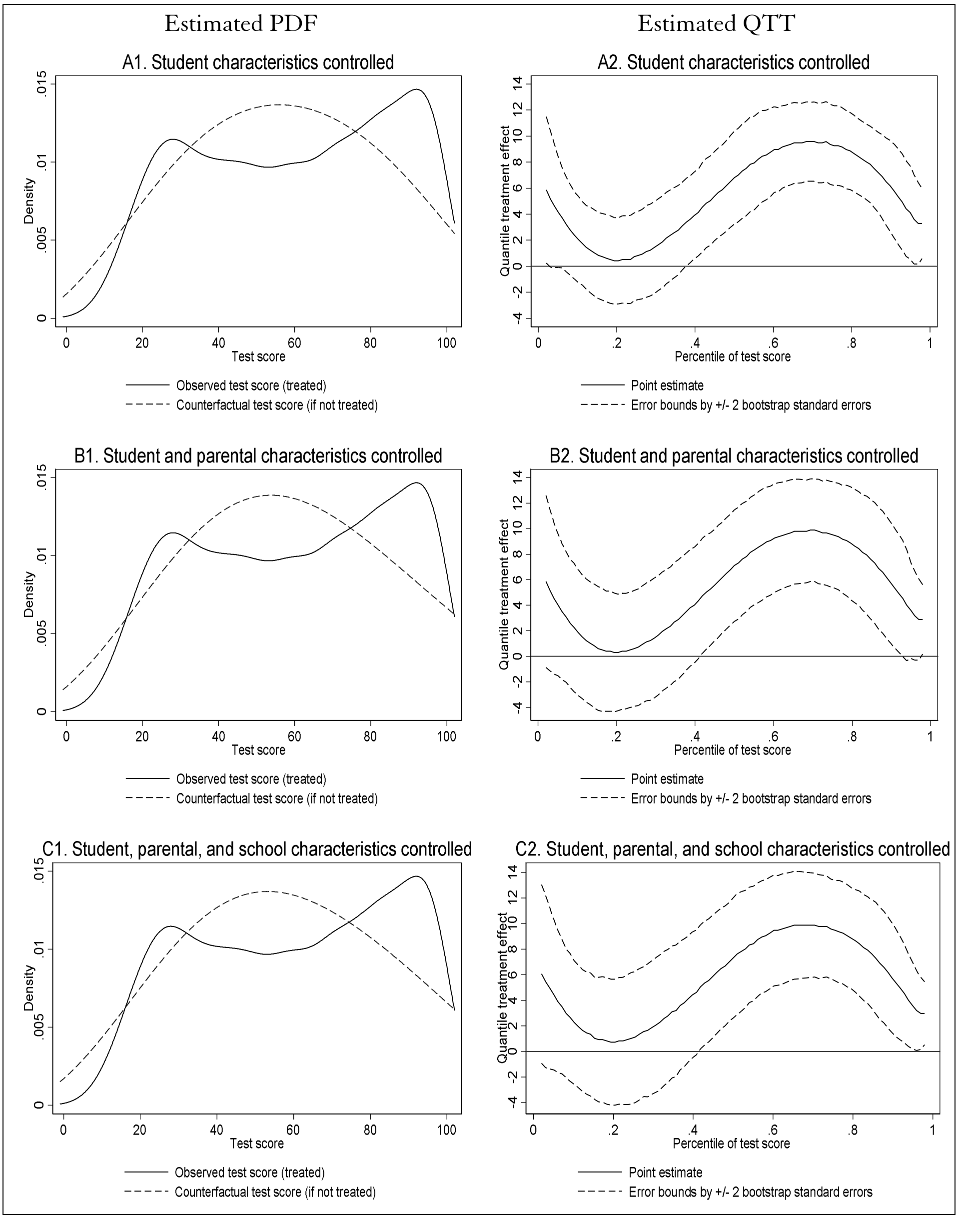
[13] When estimating the density of $Y_{i2}\,|\,D_i=1$, we use the Gaussian kernel with the rule of sum bandwidth suggested by Silverman (1986).

[Figure 1] Distributional Effects of Private Tutoring (Korean)



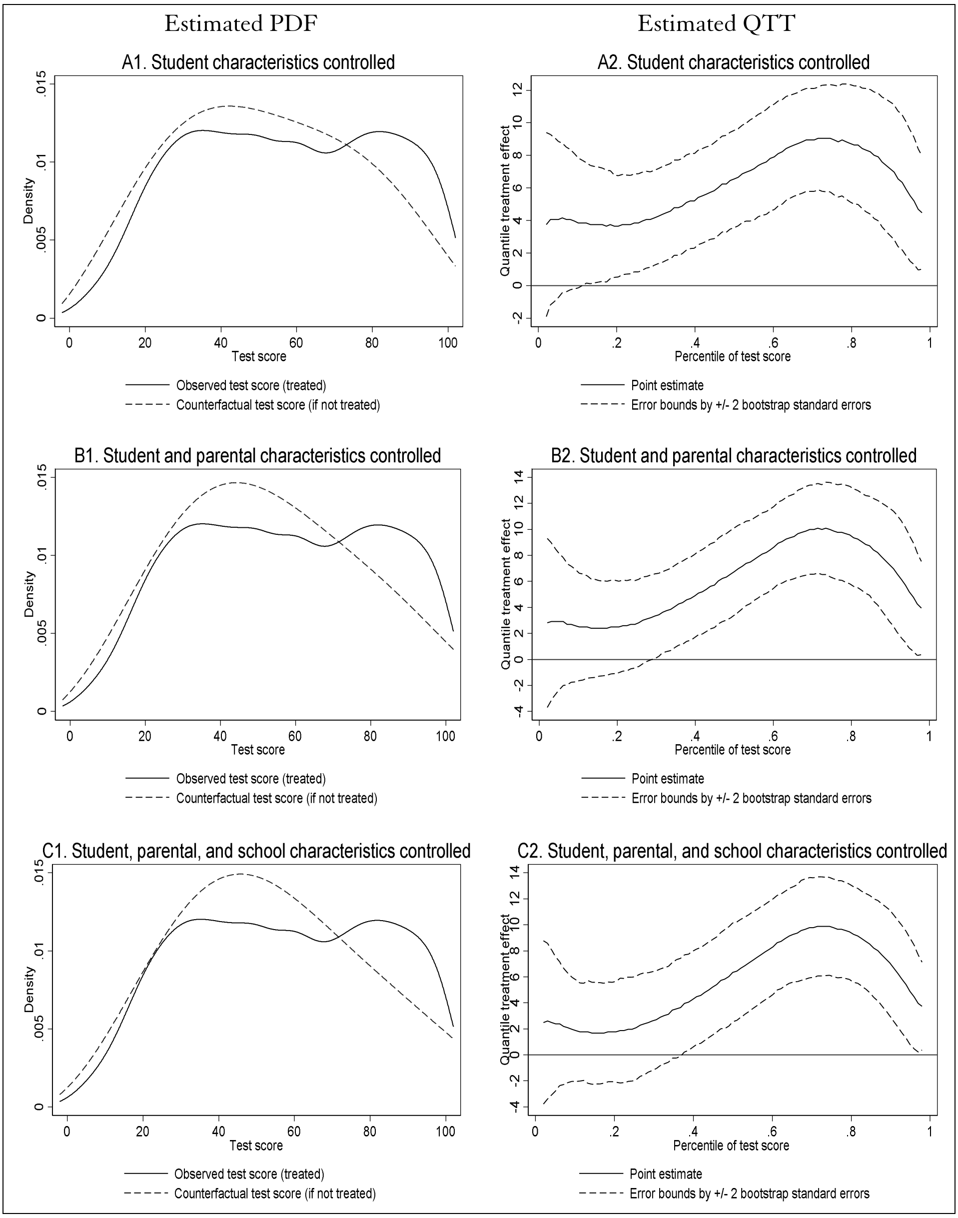
Note. The outcome variable is achievement test scores measured in November 2007. The treatment variable is an indicator for having ever received private tutoring in 2007. The same covariates used in Table 4 are controlled for. Plots in the left column compare density estimates for the realized test score distribution of the treatment group (students receiving private tutoring in 2007) with those for the counterfactual test score distribution of the same students had they not received private tutoring. Plots in the right column report estimated quantile treatment effect on the treated (QTT). Standard errors for the QTT estimates are computed by bootstrap of 2000 iterations.

[Figure 2] Distributional Effects of Private Tutoring (English)



Note. The outcome variable is achievement test scores measured in November 2007. The treatment variable is an indicator for having ever received private tutoring in 2007. The same covariates used in Table 4 are controlled for. Plots in the left column compare density estimates for the realized test score distribution of the treatment group (students receiving private tutoring in 2007) with those for the counterfactual test score distribution of the same students had they not received private tutoring. Plots in the right column report estimated quantile treatment effect on the treated (QTT). Standard errors for the QTT estimates are computed by bootstrap of 2000 iterations.

[Figure 3] Distributional Effects of Private Tutoring (Math)



Note. The outcome variable is achievement test scores measured in November 2007. The treatment variable is an indicator for having ever received private tutoring in 2007. The same covariates used in Table 4 are controlled for. Plots in the left column compare density estimates for the realized test score distribution of the treatment group (students receiving private tutoring in 2007) with those for the counterfactual test score distribution of the same students had they not received private tutoring. Plots in the right column report estimated quantile treatment effect on the treated (QTT). Standard errors for the QTT estimates are computed by bootstrap of 2000 iterations.

By integrating the estimated densities in Figures 1, 2, and 3 over the range of test scores, we calculate the estimated CDFs of $Y_{i2} \mid D_i = 1$ and $Y_{i2}^0 \mid D_i = 1$ for each of the three subjects. Given the results, we estimate the quantile treatment effects on the treated (QTT) in Equation (9) by

$$\widehat{QTT}(\tau) = \hat{F}^{-1}_{Y_{i2}|D_i=1}(\tau) - \hat{F}^{-1}_{Y_{i2}^0|D_i=1}(\tau), \tau \in (0,1), \tag{14}$$

where $\hat{F}_W^{-1}(\cdot)$ denotes the inverse of the estimated CDF of a random variable W. We compute standard errors of the $\widehat{QTT}(\tau)$ by bootstrapping with 2,000 iterations.[14]

The estimation results for Equation (14) are in the right columns of Figures 1, 2, and 3. As in the average effects, the patterns of the distributional effects for Korean are different from those for English and math. Recall that the average effects of receiving private tutoring on Korean test scores are statistically indistinguishable from zero. Similarly, we find no statistically significant effect throughout the Korean test score distribution, either. This finding suggests that private tutoring has negligible effects on Korean test scores homogenously across students with different levels of academic quality, not significantly affecting the distribution of Korean test scores.

As opposed to the results for Korean, the estimation results for English and math reveal important heterogeneity in the effects of private tutoring that is not captured by simply looking at its average effects. Regardless of the choice of the covariate specifications, the quantile treatment effects are at most modest or statistically insignificant at lower tails of the test score distribution. However, the effects become positive and statistically significant in the middle of the distribution and largest around the 70th to 80th percentiles where they amount to approximately 10 points. After reaching their peaks, the effects revert to modest or statistically insignificant levels as moving up to upper tails of the test score distribution. This finding may be because students at the top of the distribution have already scored almost 100 points, the maximum possible points of the achievement tests, before they receive the treatment. Therefore, any potential positive treatment effects for these top students cannot be captured by their achievement test scores. For example, the 90th percentiles of the baseline test scores of the students in the treatment group are 94 and 90 points in English and math, respectively. In sum, the QTT estimation results imply that private tutoring helps students at the upper half of the test score distribution but not much those at the lower half of the distribution. This finding suggests that private tutoring mainly facilitates learning processes of students in

[14] Following Hall (1992) and Horowitz (2001), when estimating the bootstrap standard errors, we use a four-times larger trimming parameter (i.e., undersmoothing) than the one chosen to compute the point estimates in Equation (12).

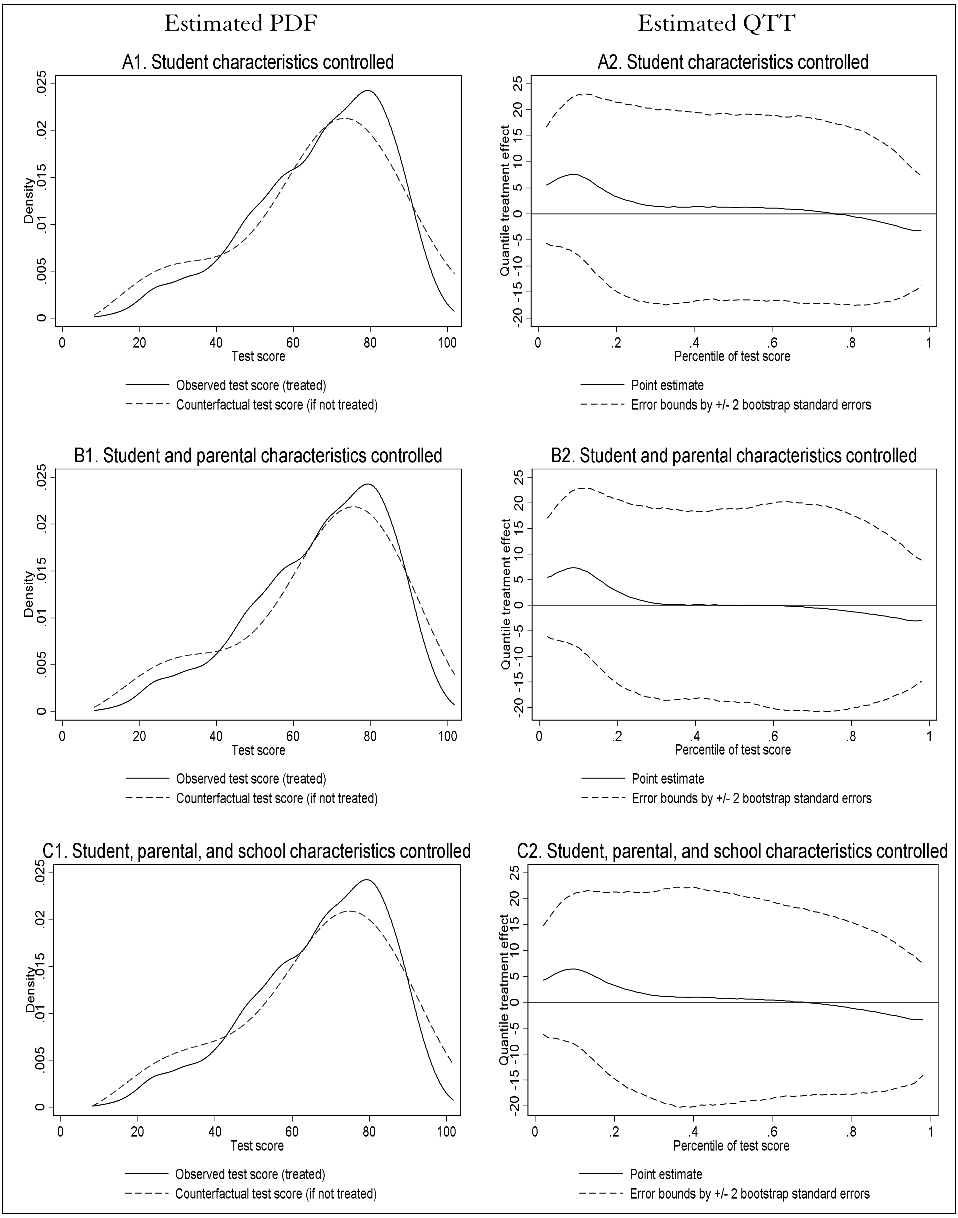
good standing rather than serving as a remedial educational measure for students who are left behind, further widening the existing outcome gap across students.

[Table 5] Falsification Test Results: Average Effects of Private Tutoring

Dependent variable:	Specifications		
Test scores in 2005	(1)	(2)	(3)
A. Subject: Korean			
Estimated ATT	.178	.110	.090
(S.E.)	(.626)	(.654)	(.640)
Covariates:			
Student characteristics	Yes	Yes	Yes
Parental characteristics	No	Yes	Yes
School characteristics	No	No	Yes
Number of observations	4016	4016	4016
B. Subject: English			
Estimated ATT	-.286	-.043	-.308
(S.E.)	(.776)	(.888)	(.904)
Covariates:			
Student characteristics	Yes	Yes	Yes
Parental characteristics	No	Yes	Yes
School characteristics	No	No	Yes
Number of observations	4442	4442	4442
C. Subject: Math			
Estimated ATT	-.899	-1.19	-1.14
(S.E.)	(.911)	(1.01)	(1.03)
Covariates:			
Student characteristics	Yes	Yes	Yes
Parental characteristics	No	Yes	Yes
School characteristics	No	No	Yes
Number of observations	4515	4515	4515

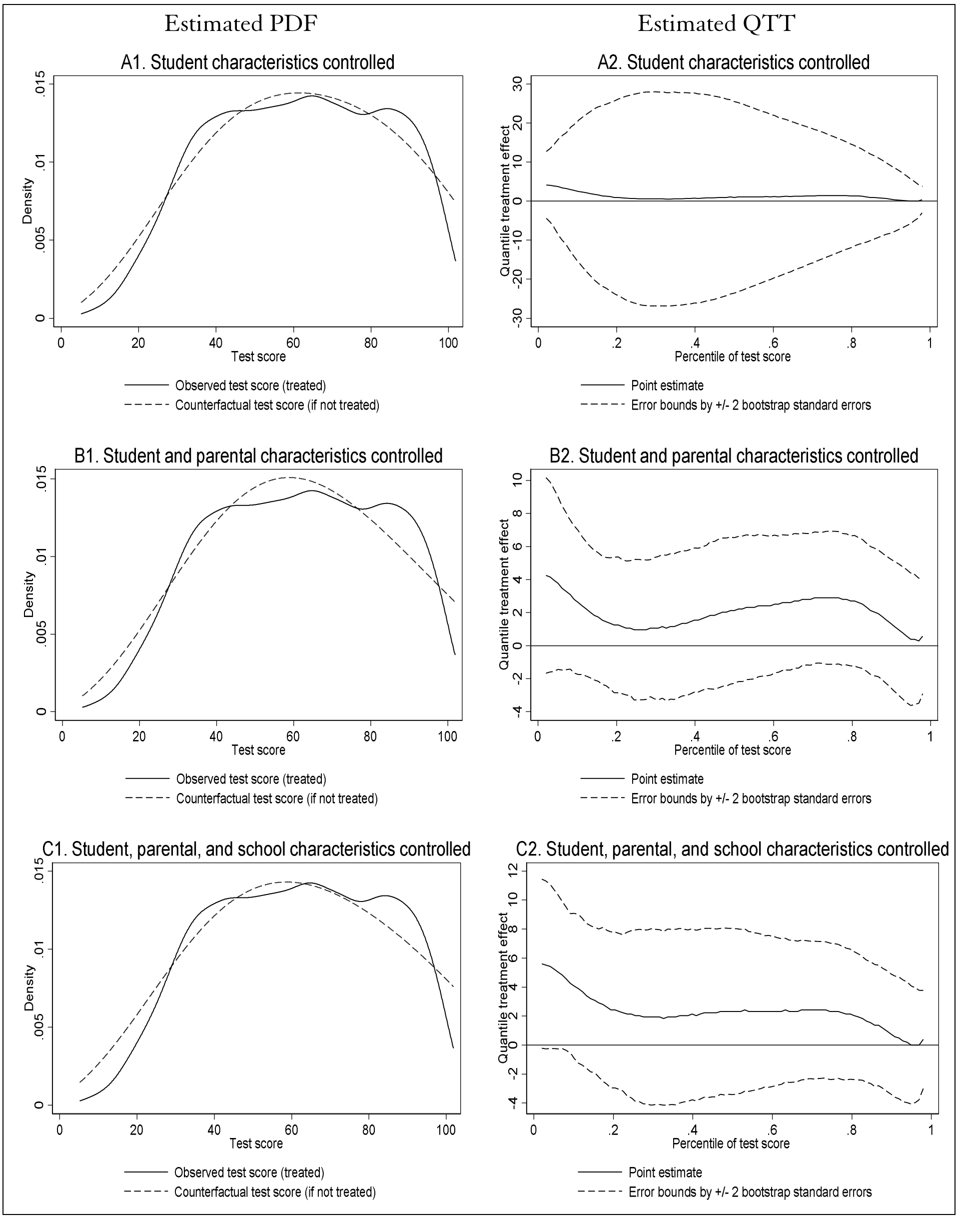
Note: The outcome variable is achievement test scores of students measured in December 2005. The treatment variable (private tutoring) is an indicator that takes 1 if a student has ever received private tutoring in 2007 and 0 otherwise. Covariates include (1) student characteristics: a dummy for having ever received private tutoring in 2006, a dummy for female, a dummy for being handicapped, number of siblings; (2) parental characteristics: parents' average age, parents' average years of education, a dummy for being married, parents' average monthly income, and a dummy for having a religion; and (3) school characteristics: a dummy for being located in a metropolitan area, a dummy for being located in a suburban area, a dummy for private school, a dummy for boy-only school, a dummy for girl-only school, logarithm of grade size, and class size. Standard errors are computed by bootstrap of 2000 iterations.

[Figure 4] Falsification Test Results: Distributional Effects of Private Tutoring (Korean)



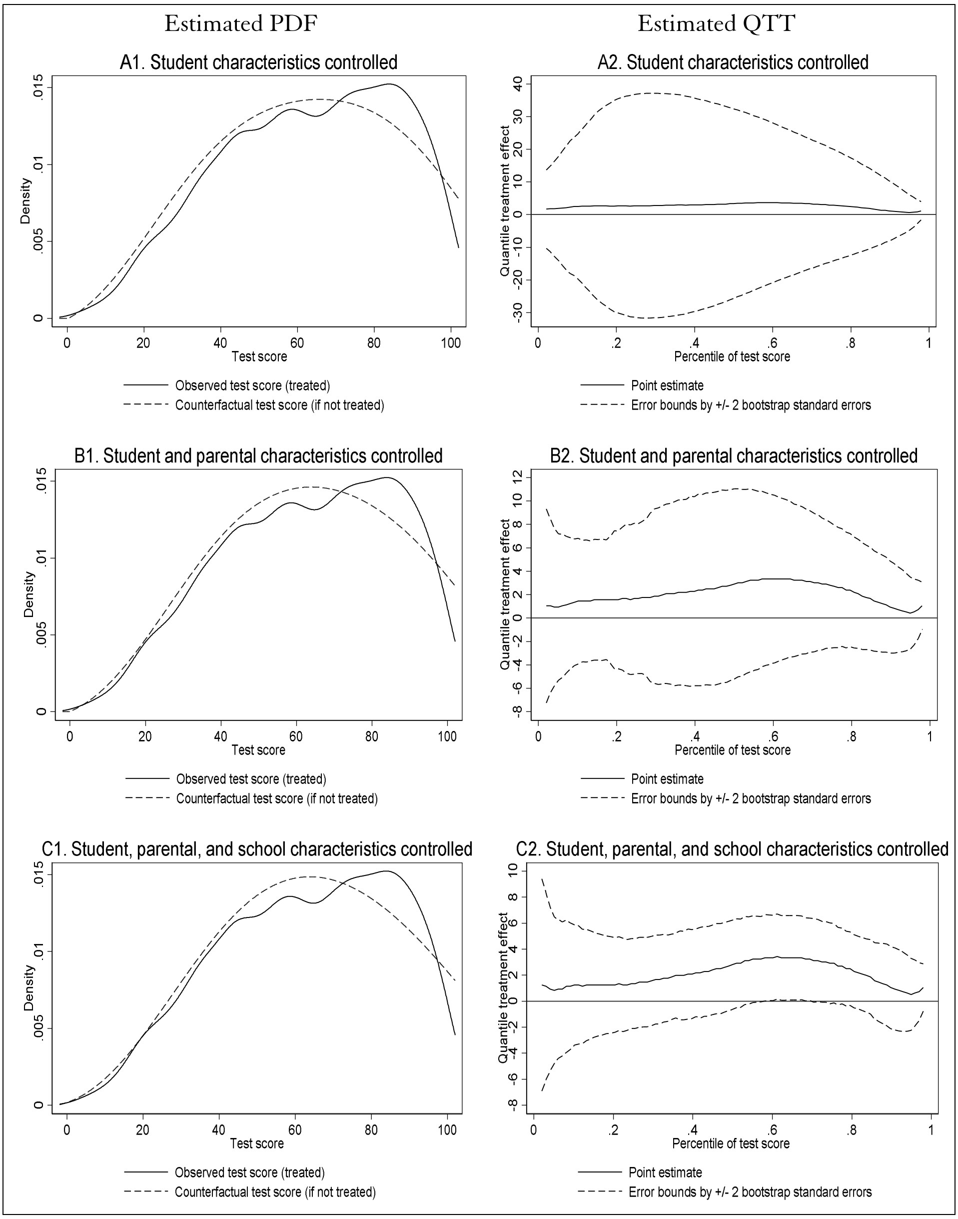
Note. The outcome variable is achievement test scores measured in December 2005. The treatment variable is an indicator for having ever received private tutoring in 2007. The same covariates used in Table 4 are controlled for. Plots in the left column compare density estimates for the realized test score distribution of the treatment group (students receiving private tutoring in 2007) with those for the counterfactual test score distribution of the same students had they not received private tutoring. Plots in the right column report estimated quantile treatment effect on the treated (QTT). Standard errors for the QTT estimates are computed by bootstrap of 2000 iterations.

[Figure 5] Falsification Test Results: Distributional Effects of Private Tutoring (English)



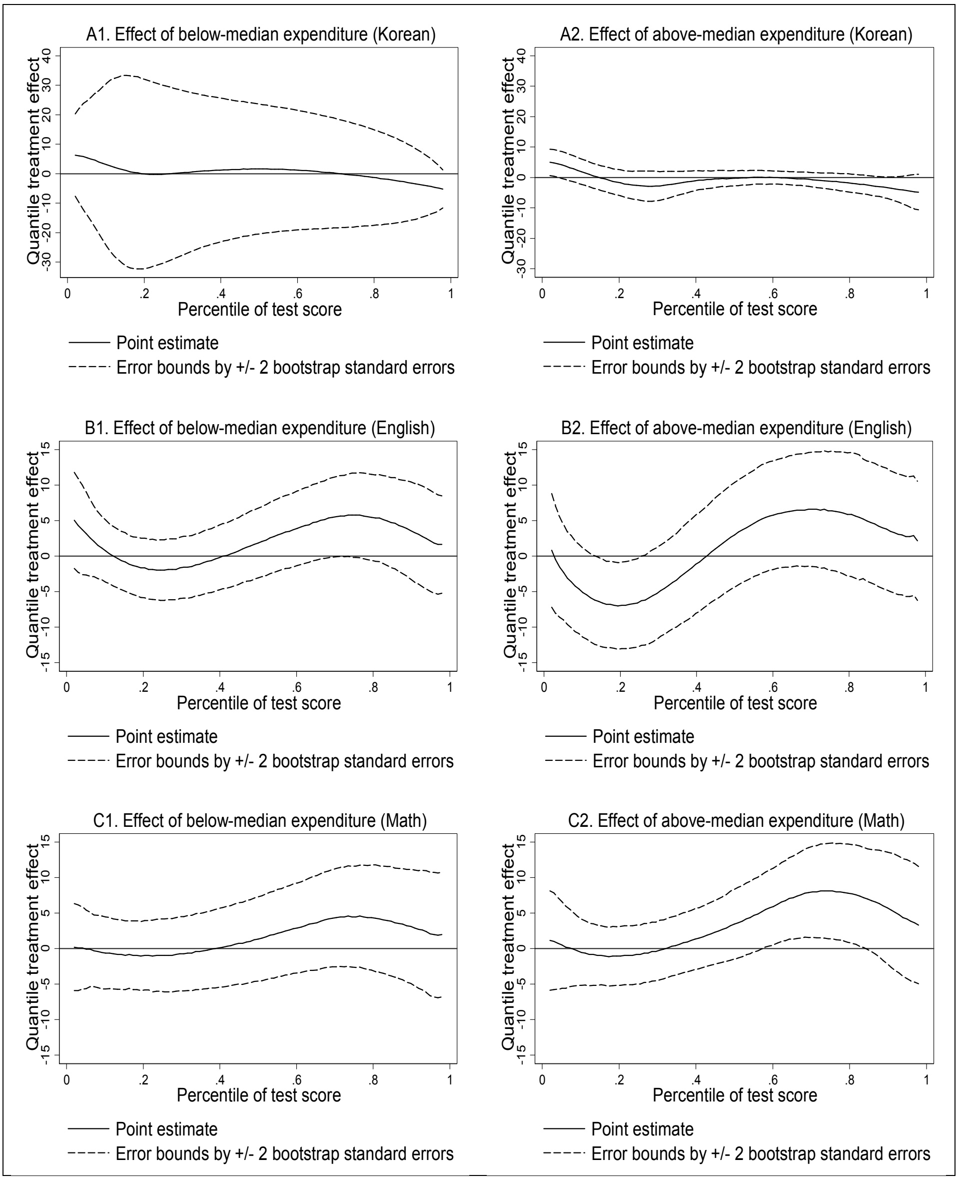
Note: The outcome variable is achievement test scores measured in December 2005. The treatment variable is an indicator for having ever received private tutoring in 2007. The same covariates used in Table 4 are controlled for. Plots in the left column compare density estimates for the realized test score distribution of the treatment group (students receiving private tutoring in 2007) with those for the counterfactual test score distribution of the same students had they not received private tutoring. Plots in the right column report estimated quantile treatment effect on the treated (QTT). Standard errors for the QTT estimates are computed by bootstrap of 2000 iterations.

[Figure 6] Falsification Test Results: Distributional Effects of Private Tutoring (Math)



Note: The outcome variable is achievement test scores measured in December 2005. The treatment variable is an indicator for having ever received private tutoring in 2007. The same covariates used in Table 4 are controlled for. Plots in the left column compare density estimates for the realized test score distribution of the treatment group (students receiving private tutoring in 2007) with those for the counterfactual test score distribution of the same students had they not received private tutoring. Plots in the right column report estimated quantile treatment effect on the treated (QTT). Standard errors for the QTT estimates are computed by bootstrap of 2000 iterations.

[Figure 7] Distributional Effects of Private Tutoring by Levels of Tutoring Expenditure



Note: The outcome variable is achievement test scores measured in November 2007. The treatment variable is an indicator for having ever received private tutoring in 2007. Student, parental, and school characteristics as in column 3 of Table 4 are controlled for. Plots in the left column report estimated quantile treatment effect on the treated (QTT) when the treatment group is restricted to students whose amount of private tutoring expenditure is below the median level. Plots in the right column report the estimated QTTs when the treatment group is restricted to students whose amount of private tutoring expenditure is greater than or equal to the median level. Standard errors for the QTT estimates are computed by bootstrap of 2000 iterations.

3. Falsification Test

To confirm that our main results in Table 4 and Figures 1, 2, and 3 are not mistakenly drawn by a model misspecification, we perform the following falsification test. We estimate the effect of receiving private tutoring in 2007 on test scores in 2005, which is determined *before* the treatment is realized and hence should not be affected by the treatment. In particular, we compute the $\widehat{ATT}$ in Equation (8) and the $\widehat{QTT}(\tau)$ in Equation (14) using the pre-determined test scores in 2005 as a new outcome variable instead of test scores in 2007.

Table 5 and Figures 4, 5, and 6 show the results of the falsification test. For all the subjects and specifications, we do not find any statistically significant effects. The estimated ATT and QTT results in Table 4 and Figures 1, 2, and 3 do not seem to be driven by model misspecifications but reflect the causal effects of private tutoring that we intend to measure.

4. Considering the Treatment Intensity

The QTT estimation results in Figures 1, 2, and 3 indicate that distributional effects of private tutoring, if any, are positive at the upper part of a test score distribution but statistically insignificant from zero at the lower part of the distribution. We interpret these results as evidence suggesting that the effect of private tutoring varies substantially across students with different levels of pre-determined academic quality. However, such observed patterns of distributional effects can also emerge simply because students at the upper part of test score distribution tend to receive a larger amount of private tutoring, but the effect of private tutoring is indeed homogenous across students with varying levels of academic quality.

To check whether the observed patterns of distributional effects reflect the *heterogeneity of treatment effect* or are simply driven by the *heterogeneity of treatment intensity*, we divide our treatment group into halves by relative treatment intensity and re-estimate the $\widehat{QTT}(\tau)$ in Equation (14) by using each of the high-intensity and low-intensity groups as a new treatment group. In particular, we divide students who receive private tutoring into those whose private tutoring expenditures are greater than the median level (high-expenditure group) and those whose expenditures are smaller than or equal to the median (low-expenditure group).[15] We then compare each of the high-expenditure and low-expenditure groups with the control (i.e., zero tutoring expenditure) group.[16]

[15] The median values of private tutoring expenditures among those who receive private tutoring are 127, 205, and 197 (in 1,000 Korean Won) for Korean, English, and math samples, respectively.

[16] A potential concern for this analysis is that a large difference may exist between the high-expenditure and the control groups' test score distributions, which may violate the common support

Figure 7 summarizes the estimation results. Regardless of the choice of treatment intensity, we find a similar pattern of distributional effects to those in Figures 1, 2, and 3. For Korean, we do not find statistically significant effects. For English and math, we find that the effect of private tutoring tend to be larger at upper percentiles of the test score distribution, although error bounds become larger probably due to smaller sample size.[17] These results suggest that the observed patterns of distributional effects in Figures 1, 2, and 3 largely demonstrate heterogeneity of treatment effects across students with different levels of academic quality rather than being simply driven by the heterogeneity of treatment intensity.

V. Conclusion

We estimate the average and distributional effects of receiving private tutoring on the academic outcomes of nationally representative middle school students in Korea during 2006–2007. We apply Bonhomme and Sauder's (2011) semiparametric estimation methods to the data and estimate the distributional effects of private tutoring, which is rarely examined by previous studies. For Korean, we fail to reject no effect throughout the entire test score distribution, which implies that private tutoring has little effects on Korean test scores and does not significantly affect the distribution of Korean test scores. For English and math, however, we find positive effects on the upper half of the test score distribution but no effects on the lower half of the distribution.

The findings of this study suggest that private tutoring mainly improves the academic outcomes of high-achieving students. To the extent that a student's academic achievement is closely related to his/her future earnings and socio-economic status, our results imply that an expansion of private tutoring in an education system likely leads to widening future socio-economic inequality more

assumption (Assumption 2). To examine this possibility, we compare the summary statistics of each of the three subgroups in Tables A2 to A4 in the Appendix. We find that, except for the private tutoring expenditures and monthly income, the characteristics of the high-expenditure group are more or less similar with those of low-expenditure group. Taking an example of predetermined (i.e., measured in 2006) math test scores, the gap between the high-expenditure and low-expenditure groups is only 0.7 (=56.5−55.8). By contrast, the gap between the low-expenditure group and the no-expenditure (i.e., the control) group amounts to 14.4 points (=55.8−41.1). This finding suggests that the plausibility of the common support assumption when comparing high-expenditure group and no-expenditure group is largely comparable to when comparing the treatment group and the control group.

[17] The main reason is that we use only half of those who receive private tutoring (i.e., students with above-median tutoring expenditures and those with below-median expenditures) as a treatment group in this section. Another reason for the reduction of the sample size is that many parents did not report the detail amount of expenditures on private tutoring for their children. Students with missing information on private tutoring expenditures are approximately 18 percent, 15 percent, and 15 percent in our Korean, English, and math samples, respectively.

than the studies measuring simple average effects suggest.

Our results that private tutoring is mainly effective for high-achieving students can also be viewed as suggesting that high-achieving students from low-income families are particularly at a disadvantage in that they are expected to benefit most from private tutoring but face the most difficulty in receiving it. This calls for policy attention for high-achieving low-income students to reach their full potential.

Appendix

[Table A1] Average Effects of Private Tutoring: Parametric Estimates

	(1)	(2)	(3)	(4)
Dependent variable:	Test scores in 2007		Difference in test scores between 2006 and 2007	
A. Subject: Korean				
Private tutoring in 2007	1.679**	0.557	0.246	0.492
	(0.654)	(0.679)	(0.518)	(0.568)
Covariates:	No	Yes	No	Yes
Observations	4,073	4,073	4,073	4,073
R-squared	0.002	0.135	0.000	0.014
B. Subject: English				
Private tutoring in 2007	18.028***	8.896***	2.327***	2.795***
	(0.830)	(0.971)	(0.617)	(0.720)
Covariates:	No	Yes	No	Yes
Observations	4,464	4,464	4,464	4,464
R-squared	0.085	0.236	0.004	0.013
C. Subject: Math				
Private tutoring in 2007	18.439***	10.316***	3.348***	4.143***
	(0.794)	(1.023)	(0.764)	(0.874)
Covariates:	No	Yes	No	Yes
Observations	4,574	4,574	4,574	4,574
R-squared	0.091	0.179	0.006	0.021

Note: Covariates refer to all the student, parental, and school characteristics listed in Table 3. Robust standard errors clustered at school level are in parentheses. Significance level: * (.10), ** (.05), *** (.001).

[Table A2] Summary Statistics by Treatment Intensity (Korean)

	High-expenditure		Low- expenditure		Control	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment (in 2007)						
Private tutoring (yes=1)	1.00	0.00	1.00	0.00	0.00	0.00
Expenditures (1000 KRW)	236	181	72.7	24.1	0.00	0.00
Outcome (in 2007)						
Test scores	56.6	21.1	61.0	19.0	57.0	21.0
Baseline characteristics (in 2006)						
Student characteristics						
Test scores	59.3	19.3	62.5	17.5	59.3	18.8
Private tutoring (yes=1)	.665	.472	.798	.401	0.296	0.456
Female (yes=1)	.435	.496	.425	.495	.550	.498
First born (yes=1)	.503	.500	.556	.497	.461	.499
Number of siblings	1.186	.715	1.166	.635	1.259	.777
Disabled (yes=1)	.021	.143	.017	.128	.020	.140
Parental characteristics						
Average age	42.2	3.7	42.1	3.6	42.6	4.5
Average years of education	13.1	2.17	13.0	2.01	12.6	2.35
Married (yes=1)	.931	.253	.931	.254	.850	.357
Monthly income (1000 KRW)	3759	2721	3507	2117	3027	2256
Having a religion (yes=1)	.706	.456	.687	.464	.670	.471
School characteristics						
Large city (yes=1)	.476	.500	.472	.499	.453	.498
Medium city (yes=1)	.456	.498	.460	.499	.433	.496
Rural area (yes=1)	.068	.251	.068	.253	.115	.319
Private school (yes=1)	.216	.412	.179	.384	.213	.409
Coed school (yes=1)	.654	.476	.630	.483	.637	.481
Boy-only school (yes=1)	.197	.398	.213	.409	.166	.372
Girl-only school (yes=1)	.149	.356	.157	.364	.197	.398
Grade size (# of students)	311	145	315	140	280	155
Class size (# of students)	35.8	5.08	35.8	4.94	35.0	5.99
Number of observations	1240		1081		1752	

[Table A3] Summary Statistics by Treatment Intensity (English)

	High- expenditure		Low- expenditure		Control	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment (in 2007)						
Private tutoring (yes=1)	1.00	0.00	1.00	0.00	0.00	0.00
Expenditures (1000 KRW)	315	266	93.5	36.2	0.00	0.00
Outcome (in 2007)						
Test scores	61.8	27.1	58.6	24.5	42.4	23.0
Baseline characteristics (in 2006)						
Student characteristics						
Test scores	62.1	24.7	59.3	22.6	45.2	20.9
Private tutoring (yes=1)	.857	.351	.884	.320	.365	.482
Female (yes=1)	.481	.500	.473	.499	.523	.500
First born (yes=1)	.546	.498	.515	.500	.417	.493
Number of siblings	1.147	.657	1.201	.645	1.312	.843
Disabled (yes=1)	.018	.134	.017	.129	.021	.144
Parental characteristics						
Average age	42.1	3.6	42.2	3.8	42.7	4.9
Average years of education	13.4	2.18	12.9	2.01	12.0	2.21
Married (yes=1)	.945	.229	.927	.260	.796	.403
Monthly income (1000 KRW)	4008	2702	3362	1764	2494	1900
Having a religion (yes=1)	.705	.456	.691	.462	.657	.475
School characteristics						
Large city (yes=1)	.497	.500	.483	.500	.401	.490
Medium city (yes=1)	.444	.497	.434	.496	.468	.499
Rural area (yes=1)	.059	.235	.083	.276	.131	.337
Private school (yes=1)	.215	.411	.180	.384	.201	.401
Coed school (yes=1)	.657	.475	.635	.482	.620	.486
Boy-only school (yes=1)	.179	.384	.194	.396	.188	.391
Girl-only school (yes=1)	.164	.370	.170	.376	.192	.394
Grade size (# of students)	326	142	308	145	261	158
Class size (# of students)	36.2	4.71	35.7	5.30	34.2	6.42
Number of observations	1910		1467		1087	

[Table A4] Summary Statistics by Treatment Intensity (Math)

	High- expenditure		Low- expenditure		Control	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment (in 2007)						
Private tutoring (yes=1)	1.00	0.00	1.00	0.00	0.00	0.00
Expenditures (1000 KRW)	328	276	93.4	36.5	0.00	0.00
Outcome (in 2007)						
Test scores	57.7	26.4	56.9	24.6	38.9	22.0
Baseline characteristics (in 2006)						
Student characteristics						
Test scores	56.5	25.0	55.8	23.1	41.1	20.9
Private tutoring (yes=1)	.854	.353	.870	.337	.368	.483
Female (yes=1)	.481	.500	.488	.500	.521	.500
First born (yes=1)	.535	.499	.529	.499	.427	.495
Number of siblings	1.140	.660	1.187	.619	1.314	.844
Disabled (yes=1)	.020	.141	.017	.130	.022	.147
Parental characteristics						
Average age	42.2	3.7	42.0	3.5	42.7	5.0
Average years of education	13.4	2.19	12.9	2.01	12.0	2.26
Married (yes=1)	.943	.231	.926	.261	.799	.401
Monthly income (1000 KRW)	4093	2710	3340	1705	2473	1851
Having a religion (yes=1)	.716	.451	.691	.462	.657	.475
School characteristics						
Large city (yes=1)	.506	.500	.475	.500	.390	.488
Medium city (yes=1)	.437	.496	.449	.498	.460	.499
Rural area (yes=1)	.057	.232	.076	.266	.150	.357
Private school (yes=1)	.218	.413	.177	.382	.202	.402
Coed school (yes=1)	.651	.477	.640	.480	.614	.487
Boy-only school (yes=1)	.185	.388	.188	.391	.187	.390
Girl-only school (yes=1)	.164	.370	.172	.377	.200	.400
Grade size (# of students)	327	141	311	146	255	158
Class size (# of students)	36.3	4.78	35.8	5.19	34.0	6.45
Number of observations	1976		1506		1092	

A1. Derivation of Equation (7)

This section illustrates how we apply the model by Bonhomme and Sauder (2011) to our study and derive Equation (7). We draw on section II.B of Bonhomme and Sauder (2011) for the following illustration of their method.

The ATT can be written as

$$\begin{aligned} ATT &= E[Y_{i2}^1 - Y_{i2}^0 \mid D_i = 1] = \int E[Y_{i2}^1 - Y_{i2}^0 \mid X_i, D_i = 1] dP(X_i \mid D_i = 1) \\ &= \int \{E[Y_{i2} \mid X_i, D_i = 1] - E[Y_{i2}^0 \mid X_i, D_i = 1]\} dP(X_i \mid D_i = 1) \end{aligned} \quad \text{(A1)}$$

where $E[Y_{i2}^0 \mid X_i, D_i = 1]$ in Equation (A1) needs to be identified. By the additive structure of the educational production function in Equations (5) and (6) and the selection on observables and time-invariant unobservables assumption (assumption 1), $E[Y_{i2}^0 \mid X_i, D_i = 1]$ is identified as

$$E[Y_{i2}^0 \mid X_{\mathrm{i}}, D_i = 1] = E[Y_{i2} \mid X_i, D_i = 0] + E[Y_{i1} \mid X_i, D_i = 1] - E[Y_{i1} \mid X_i, D_i = 0] \quad \text{(A2)}$$

Substituting (A2) into (A1), the ATT is identified as the following difference-in-differences estimand:

$$ATT = \int \{E[Y_{i2} - Y_{i1} \mid X_i, D_i = 1] - E[Y_{i2} - Y_{i1} \mid X_i, D_i = 0]\} dP(X_i \mid D_i = 1) \quad \text{(A2)}$$

Estimating Equation (A3) nonparametrically is infeasible due to the curse of dimensionality. To proceed, we use the Lemma 3.1 in Abadie (2005) following Bonhomme and Sauder (2011). Under the selection on observables and time-invariant unobservables assumption (assumption 1) and the common support assumption (assumption 2), Abadie (2005) show that

$$E[Y_{i2}^1 - Y_{i2}^0 \mid X_i, D_i = 1] = E[\omega_i \left(Y_{i2} - Y_{i1}\right) \mid X_i], \quad \text{(A3)}$$

where

$$\omega_i = \frac{D_i - P[D_i = 1 \mid X_i]}{P[D_i = 1 \mid X_i] P[D_i = 0 \mid X_i]} \quad \text{(A4)}$$

Summing (A3) over the conditional distribution of $X_i \mid D_i = 1$, the ATT can be written as (Abadie 2005)

$$ATT = \int E[\omega_i \left(Y_{i2} - Y_{i1}\right) \mid X_i] dP(X_i \mid D_i = 1)$$

$$=\int E[\omega_i\left(Y_{i2}-Y_{i1}\right)\mid X_i]\frac{\Pr[D_i=1\mid X_i]}{\Pr[D_i=1]}dP(X_i)$$

$$=\frac{1}{\Pr[D_i=1]}\int E[\omega_i \Pr[D_i=1\mid X_i](Y_{i2}-Y_{i1})\mid X_i]dP(X_i)\,. \tag{A5}$$

Substituting (A4) into (A5) yields Equation (7).

A2. Derivation of Equation (10)

This section illustrates how we apply the model of Bonhomme and Sauder (2011) to our study and derive Equation (10). We draw on section II.B of Bonhomme and Sauder (2011) for the following illustration of their method.

For any real-valued random variable W, its probability density function can be obtained by the following inverse Fourier transformation of its characteristic function, $\Psi_W(t)\equiv E[\exp(jtW)]$:

$$f_W(w)=\frac{1}{2\pi}\int_{-\infty}^{\infty}\exp(-jtw)\Psi_W(t)dt\,, \tag{A6}$$

where $j=\sqrt{-1}$ and $t\in R$. Hence, identifying the characteristic function of $Y_{i2}^0\mid D_i=1$ suffices the identification of its density.

Let $\Psi_{Y_{i2}^0|D_i=1}(t)$ denote the characteristic function of $Y_{i2}^0\mid D_i=1$. By definition,

$$\Psi_{Y_{i2}^0|D_i=1}(t)=E[\exp(jtY_{i2}^0)\mid D_i=1]=\int\Psi_{Y_{i2}^0|D_i=1,X_i}(t\mid X_i)dP(X_i\mid D_i=1) \tag{A7}$$

Bonhomme and Sauder (2011; Theorem 2) show that when educational production functions take the form of Equations (5) and (6) and Assumptions 1, 2, and 3 hold, the conditional characteristic function of the counterfactual $Y_{i2}^0\mid D_i=1$ is identified as a function of three conditional characteristic functions of the realized $Y_{i2}\mid D_i=0$, $Y_{i1}\mid D_i=1$, and $Y_{i1}\mid D_i=0$.

$$\Psi_{Y_{i2}^0|D_i=1,X_i}(t\mid x)=\frac{\Psi_{Y_{i1}|D_i=1,X_i}(t\mid x)}{\Psi_{Y_{i1}|D_i=0,X_i}(t\mid x)}\Psi_{Y_{i2}|D_i=0,X_i}(t) \tag{A8}$$

Substituting (A8) into (A7) yields

$$\Psi_{Y_{i2}^0|D_i=1}(t)=\int\frac{\Psi_{Y_{i1}|D_i=1,X_i}(t\mid x)}{\Psi_{Y_{i1}|D_i=0,X_i}(t\mid x)}\Psi_{Y_{i2}|D_i=0,X_i}(t\mid x)dP(X_i\mid D_i=1)$$

$$= \int \frac{\Psi_{Y_{i1}|D_i=1,X_i}(t|x)}{\Psi_{Y_{i1}|D_i=0,X_i}(t|x)} \Psi_{Y_{i2}|D_i=0,X_i}(t|x) \frac{P(D_i=1|X_i)}{P(D_i=1)} dP(X_i)$$

$$= \frac{1}{P(D_i=1)} \int \frac{P(D_i=1|X_i)}{P(D_i=0|X_i)} \frac{\Psi_{Y_{i1}|D_i=1,X_i}(t|x)}{\Psi_{Y_{i1}|D_i=0,X_i}(t|x)} \Psi_{Y_{i2}|D_i=0,X_i}(t|x) P(D_i=0|X_i) dP(X_i) \quad \text{(A9)}$$

It holds that

$$\Psi_{Y_{i2}|D_i=0,X_i}(t|x) P(D_i=0|X_i) = E[\exp(jtY_{i2})|D_i=0,X_i] P(D_i=0|X_i)$$
$$= E[(1-D_i)\exp(jtY_{i2})|X_i] \quad \text{(A10)}$$

Similarly,

$$\Psi_{Y_{i1}|D_i=0,X_i}(t|x) P(D_i=0|X_i) = E[(1-D_i)\exp(jtY_{i1})|X_i] \quad \text{(A11)}$$
$$\Psi_{Y_{i1}|D_i=1,X_i}(t|x) P(D_i=1|X_i) = E[D_i \exp(jtY_{i1})|X_i] \quad \text{(A12)}$$

Substituting (A10), (A11), and (A12) into (A9) yields

$$\Psi_{Y_{i2}^0|D_i=1}(t) = \frac{1}{p_D} E[\omega(t|X_i)(1-D_i)\exp(jtY_{i2})], \quad \text{(A13)}$$

where

$$\omega(t|X_i) \equiv \frac{E[D_i \exp(jtY_{i1})|X_i]}{E[(1-D_i)\exp(jtY_{i1})|X_i]} \quad \text{(A14)}$$

Substituting Equation (A13) into Equation (A6) yields Equation (10).

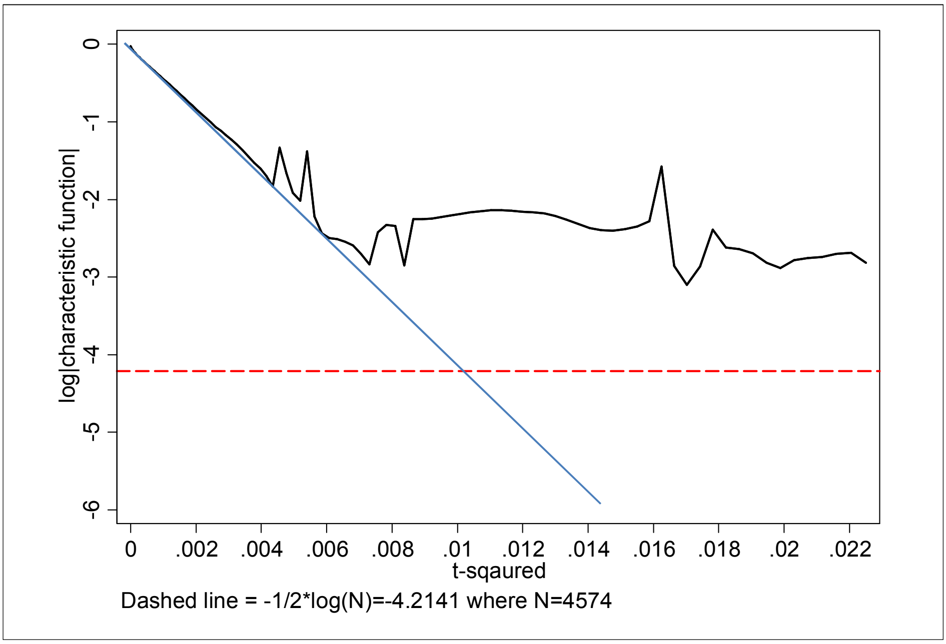
A3. Choice of the truncation parameter in Equation (12)

According to Diggle and Hall (1993), an optimal T_N must satisfy (Bonhomme and Sauder, 2011)

$$\log|\hat{\Psi}_{Y_{i2}^0|D_i=1}(T_N)| = -\frac{1}{2}\log N \quad \text{(A15)}$$

Figure A1 plots the estimated $\log|\hat{\Psi}_{Y_{i2}^0|D_i=1}(t)|$ against t^2 for the math sample when the student, parental, and school characteristics are used as covariates. Following Bonhomme and Sauder (2009, 2011), we extrapolate the (almost) linear part of $\log|\hat{\Psi}_{Y_{i2}^0|D_i=1}(t)|$ and find the value of t where the extrapolated line crosses $-\frac{1}{2}\log N$. This yields $t \approx \sqrt{.010} = .100$, which we use as the T_N. For other subject samples and covariate specifications, we determine T_N in a similar way.

[Figure A1] Log of the Absolute Value of the Estimated Characteristic Function



References

Abadie, A. (2005), "Semiparametric Difference-in-differences Estimators," *The Review of Economic Studies*, Vol. 72, No. 1, 1–19.

Altonji, J. G., T. E. Elder, and C. R. Taber (2005), "Selection on Observed and Unobserved Variables: Assessing the Effectiveness of Catholic schools," *Journal of Political Economy*, Vol. 113, No. 1, 151–184.

Altonji, J. G., T. E. Elder, and C. R. Taber (2008), "Using Selection on Observed Variables to Assess Bias from Unobservables When Evaluating Swan-Ganz Catheterization," *The American Economic Review*, Vol. 98, No. 2, 345–350.

Bedard, K. (2003), "School Quality and the Distribution of Male Earnings in Canada," *Economics of Education Review*, Vol. 22, No. 4, 395–407.

Bonhomme, S., and U. Sauder (2011), "Recovering Distributions in Difference-in-differences Models: A Comparison of Selective and Comprehensive Schooling," *The Review of Economics and Statistics*, Vol. 93, No. 2, 479–494.

Bray, M., and P. Kwok (2003), "Demand for Private Supplementary Tutoring: Conceptual Considerations, and Socio-economic Patterns in Hong Kong," *Economics of Education Review*, Vol. 22, No. 6, 611–620.

Bray, M., A. E. Mazawi, and R. G. Sultana (2013), *Private Tutoring across the Mediterranean: Power Dynamics and Implications for Learning and Equity*, Comparative and International Education: A Diversity of Voices, Vol. 25, Sense Publishers: Rotterdam, The Netherlands.

Briggs, D. C. (2001), "The Effect of Admissions Test Preparation: Evidence from NELS: 88," *Chance*, Vol. 14, No. 1, 10–18.

Buchmann, C., D. J. Condron, and V. J. Roscigno (2010), "Shadow Education, American Style: Test Preparation, the SAT, and College Enrollment," *Social Forces*, Vol. 89, No. 2, 435–461.

Card, D., and A. B. Krueger (1996), "School Resources and Student Outcomes: An Overview of the Literature and New Evidence from North and South Carolina," *The Journal of Economic Perspectives*, Vol. 10, No. 4, 31–50.

Cheo, R., and E. Quah (2005), "Mothers, Maids and Tutors: An Empirical Evaluation of Their Effect on Children's Academic Grades in Singapore," *Education Economics*, Vol. 13, No. 3, 269–285.

Corak, M., and D. Lauzon (2009), "Differences in the Distribution of High School Achievement: The Role of Class-size and Time-in-term," *Economics of Education Review*, Vol. 28, No. 2, 189–198.

Dang, H. (2007) "The Determinants and Impact of Private Tutoring Classes in Vietnam," *Economics of Education Review*, Vol. 26, No. 6, 683–698.

Diggle, P. J., and P. Hall. (1993), "A Fourier Approach to Nonparametric Deconvolution of a Density Estimate," *Journal of the Royal Statistical Society, Series B (Methodological)*, Vol. 55, No. 2, 523–531.

Eide, E. R., M. H. Showalter, and D. P. Sims (2002), "The Effects of Secondary School Quality on the Distribution of Earnings," *Contemporary Economic Policy*, Vol. 20, No.

2, 160–170.

Europe Industry News (2019), http://europeindustrynews.com/19781/global-private-tutoring-mar ket-prediction-usd-177621-million-by-2026/

Guryan, J. (2001), "Does Money Matter? Regression-Discontinuity Estimates from Education Finance Reform in Massachusetts," National Bureau of Economic Research Working Paper, No. 8269, National Bureau of Economic Research, Cambridge: MA.

Gurun, A., and D. L. Millimet (2008), "Does Private Tutoring Payoff?" IZA Discussion Paper, No. 3637, The Institute for the Study of Labor (IZA), Bonn, Germany.

Ha, T. T., and T. Harpham (2005), "Primary Education in Vietnam: Extra Classes and Outcomes," *International Education Journal*, Vol. 6, No. 5, 626–634.

Hall, P. (1992), "Effect of Bias Estimation on Coverage Accuracy of Bootstrap Confidence Intervals for a Probability Density," *Annals of Statistics*, Vol. 20, No. 2, 675-694.

Hanushek, E. A. (1986), "The Economics of Schooling: Production and Efficiency in Public Schools," *Journal of Economic Literature*, Vol. 24, No. 3, 1141–1177.

Horowitz, J. L. (2001), "The Bootstrap," *Handbook of Econometrics*, Vol. 5, ed: J. J. Heckman and E. E. Leamer, Elsevier.

Kang, C. (2007), "Does Money Matter? The Effect of Private Educational Expenditures on Academic Performance," Working Paper no.0704, Department of Economics, National University of Singapore, Singapore.

Krueger, A. B. (2003), "Economic Considerations and Class Size," *The Economic Journal*, Vol. 113, F34–F63.

Krueger, A. B., and D. M. Whitmore. (2001), "The Effect of Attending a Small Class in the Early Grades on College-test Taking and Middle School Test Results: Evidence from Project STAR," *Economic Journal*, Vol. 111, 1–28.

Lamarche, C. (2008), "Private School Vouchers and Student Achievement: A Fixed Effects Quantile Regression Evaluation," *Labour Economics*, Vol. 15, No. 4, 575–590.

Lee, J., Y. Kim, and C. Yoon. (2004), "The Effects of Pre-class Tutoring on Student Achievement: Challenges and Implications for Public Education in Korea," *KEDI Journal of Educational Policy*, Vol. 1, No. 1, 25–42.

Loyalka, P., and A. Zakharov (2016), "Does Shadow Education Help Students Prepare for College? Evidence from Russia," *International Journal of Educational Development*, Vol. 49(C), 22–30.

Manski, C. F., and J. V. Pepper (2000), "Monotone Instrumental Variables: with an Application to the Returns to Schooling," *Econometrica*, Vol. 68, No. 4, 997–1010.

Maasoumi, E., D. L. Millimet, and V. Rangaprasad (2005), "Class Size and Educational Policy: Who Benefits from Smaller Classes?" *Econometric Reviews*, Vol. 24, No. 4, 333–368.

McEwan, P. J. (2004), "The Potential Impact of Vouchers," *Peabody Journal of Education*, Vol. 79, No. 3, 57–80.

Ono, H. (2007), "Does "Examination Hell" Pay Off? A Cost–Benefit Analysis of "Ronin" and College Education in Japan," *Economics of Education Review*, Vol. 26, No. 3, 271–284.

Park, Y. (2013), *Essays in Empirical Microeconomics*, Doctoral Dissertation, Princeton

University, Princeton, NJ, U.S.A. (http://arks.princeton.edu/ark:/88435/dsp01j098zb23z)

Ryu, D., and C. Kang (2013), "Do Private Tutoring Expenditures Raise Academic Performance? Evidence from Middle School Students in South Korea," *Asian Economic Journal*, Vol. 27, No. 1, 59–83.

Sadoff, S. (2014), "The Role of Experimentation in Education Policy," *Oxford Review of Economic Policy*, Vol. 30, No. 4, 597–620.

Silova, I. (2010), "Private Tutoring in Eastern Europe and Central Asia: Policy Choices and Implications," *Compare*, Vol. 40, No. 3, 327–344.

Silverman, B. W. (1986), *Density Estimation for Statistics and Data Analysis*, London, U.K.: Chapman & Hall.

Stevenson, D. L., and D. P. Baker (1992), "Shadow Education and Allocation in Formal Schooling: Transition to University in Japan," *American Journal of Sociology*, Vol. 97, No. 6, 1639–1657.

Tansel, A., and F. Bircan (2005), "Effect of Private Tutoring on University Entrance Examination Performance in Turkey," IZA Discussion Paper, No.1609, The Institute for the Study of Labor (IZA), Bonn, Germany.

사교육과 학생의 학업성취도 분포: 교육 불평등에 대한 사교육의 함의*

강 창 희** · 박 윤 수***

논문초록 사교육이 세계적으로 확산됨에 따라 사교육의 확대가 교육 불평등을 악화시키고 궁극적으로 세대 간 이동성을 악화시킬 것이라는 우려가 많다. 본 연구는 사교육이 한국 중학생의 학업성취도에 미치는 평균 및 분포 효과를 추정하여 이 질문에 답하고자 한다. 이중차분모형에서 분포를 복구하는 반모수적 모형을 적용한 결과, 사교육은 성취도 분포의 상단을 우측으로 이동시키면서 분포의 하단에서는 통계적으로 유의하지 않은 영향을 미친 것으로 나타났다. 이상의 결과는 사교육의 확대가 교육 불평등을 심화시키는 정도가 사교육의 평균 효과가 미미하다는 실증연구들이 시사하는 수준보다 클 수 있음을 시사한다.

핵심 주제어: 사교육, 학업성취도, 교육 불평등, 분위처치효과
경제학문헌목록 주제분류: I24, C21

투고 일자: 2020. 3. 2. 심사 및 수정 일자: 2020. 11. 26. 게재 확정 일자: 2021. 2. 19.

* 본 연구는 Park (2013)의 제 3장을 바탕으로 작성되었음.

** 제1저자, 중앙대학교 경제학부 교수, e-mail: ckang@cau.ac.kr. 강창희의 연구는 서울대 경제연구소 분배정의연구센터와 한국연구재단의 연구지원(NRF-2016S1A3A2924944)을 통해 이루어졌습니다.

*** 교신저자, 숙명여자대학교 경상대학 경제학부 조교수, e-mail: yoonpark@sm.ac.kr. 본 연구는 숙명여자대학교 교내연구비지원에 의해 수행되었음(과제번호 1-2003-2014).