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The Effects of Supplementary Tutoring on Students' Mathematics Achievement in Japan and the United States[1]

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ABSTRACT

Supplementary tutoring, also known as shadow education, private tutoring, or out-of-school tutoring, refers to a range of organized tutoring practices in academic subjects that occur outside regular school hours. This study used the 2006 Programme for International Student Assessment (PISA) and compared between the United States and Japan, two countries with different patterns of dominant use of supplementary tutoring. The study addressed the following three questions: (1) What factors affect students' participation in supplementary tutoring in the United States and Japan? (2) What are the effects of supplementary tutoring on students' mathematics achievement in the two countries? (3) Do the effects differ by student subgroups in each country? This study distinguished between two types of supplementary tutoring: out-of-school tutoring (taught by non-school teachers) and school-tutoring (taught by schoolteachers). The study used propensity score matching as an analytic strategy, which created counterfactual groups that were as similar as possible to facilitate comparison between the treated and controlled subjects. Nearest-neighbor method, stratification method, and kernel method were used along with the conventional OLS method. Regarding the background of participation, supplementary tutoring in Japan was largely represented by out-of-school tutoring as a private service, used by middle-class students for obtaining academic excellence. In contrast, supplementary tutoring in the United States was typically represented by in-school tutoring as a social service, used by low-achieving students in low-SES schools for ensuring minimum proficiency. The study obtained no statistically significant estimates of the effects of either type of tutoring in two countries. These results suggested that while the students' opportunities to receive tutoring varied, the overall academic consequences of tutoring did not vary among students. Methodological issues in using propensity score methods were identified in the study, and their implications for meeting causal assumptions were discussed.

Chapter 1
INTRODUCTION

Beyond school hours, many students across the world engage in supplementary tutoring. Supplementary tutoring, also known as shadow education, private tutoring, or out-of-school tutoring, refers to a range of organized tutoring practices in academic subjects that occur outside regular school hours. Whether at school, home, commercial institutions or community organizations, students receive extra lessons in academic subjects to support their learning in formal schools. While schools continue to serve as the primary institution for educating children, the prevalence of supplementary tutoring suggests that learning also takes place outside school. By engaging in supplementary tutoring of various forms, students may deepen their understanding of school subjects, enhance their daily academic performance, or practice for system-wide standardized tests and national examinations.

Today, supplementary tutoring exists all over the world (Baker et al., 2001; Bray 1999). For example, it has existed for decades in Japan, where more than half of today's middle school students receive some type of academic tutoring outside school (Monbukagakusho, 2008). Families pay for tutoring, expecting these extra lessons to increase their children's academic achievement. In the United States, supplementary tutoring was relatively unknown in the past. However, it has grown over the past decades, especially under the No Child Left Behind (NCLB) legislation that uses such out-of-school lessons to boost students' academic achievement. Indeed, tutoring practices have experienced a rapid expansion in the U.S. due to the competitive pressure of high-stakes achievement tests (Russell 2002; Stotsky et al., 2010; Sullivan, 2010).

Across societies, many students receive such services, expecting tutoring lessons to have some positive academic impact. However, researchers have only begun to address the issue of the causal effect of supplementary tutoring in recent years (Briggs, 2001; Heinrich et al., 2010; Kuan, 2011; Lauer et al., 2006). Research findings on the effectiveness of supplementary tutoring remain inconclusive to date. In particular, only a handful of studies have adequately addressed the methodological problem of selection bias. Selection is the key issue in estimating the causal effect of supplementary tutoring, because students who receive supplementary tutoring are likely to be selected according to their characteristics, including prior academic achievement,

socioeconomic status, and motivation. Failure to control for these factors may bias estimates of the causal effect of tutoring.

Specifically, two types of selection may be found in student participation in supplementary tutoring. One is positive selection when high-SES students are more likely to engage in supplementary tutoring. This is the case in Japan, where middle-class students engage in tutoring on a private basis (Mori & Baker, 2010; Stevenson & Baker, 1992; Yamamoto & Brinton, 2010). The other is negative selection when low-SES students are more likely to engage in supplementary tutoring. This is the case in the United States, where poor and underachieving students tend to receive tutoring lessons via public funding (U.S. Department of Education, 2007; Weiss et al., 2009). As these examples suggest, students' participation in supplementary tutoring is often affected by various selection factors for different countries. Causal effect of supplementary tutoring on educational outcomes needs to be examined after approximately controlling for such selection.

In addition to addressing selection for the overall group of students, causal effects may vary by student subgroups. Previous studies have suggested that the effect of supplementary tutoring may be stronger for certain types of students who may derive greater benefits from it than other students (Kuan, 2011; Lauer et al., 2006). When populations are heterogeneous, estimates of the causal effect corrected for selection bias may not be applicable to the overall group.

Purpose of the Study

The purpose of this study is to examine whether and how supplementary tutoring increases students' academic achievement. I focus on two countries that have different patterns of selection in supplementary tutoring: the United States and Japan. I also examine heterogeneous effects by student subgroups. More specifically, I ask the following questions: (1) What factors affect students' participation in supplementary tutoring in the United States and Japan? (2) What are the effects of supplementary tutoring on students' mathematics achievement in the two countries? (3) Do the effects differ by student groups in each country?

Organization of the this Paper

The structure of this paper is as follows. In chapter 2, I will review relevant literature in order to provide empirical and theoretical perspectives on the background and effect of supplementary tutoring. In chapter 3, I will describe data and variables for the study and introduce propensity score matching as an analytic strategy. In chapter 4, I will show the results of my analysis and interpret the findings. In the final chapter, I will summarize the findings, discuss methodological and policy implications of the study, and provide recommendations for future research.

Chapter 2
LITERATURE REVIEW

In this chapter, I first introduce two existing bodies of research on supplementary tutoring: shadow education/private tutoring, and out-of-school-time lessons/afterschool tutoring. By reviewing these two research trends, I distinguish some key dimensions of supplementary tutoring described in each literature. I then introduce single-country studies and multiple-country studies on supplementary tutoring to explain how researchers have investigated this phenomenon worldwide. Following these reviews, I introduce empirical studies on the factors that affect students' participation in tutoring. I then examine theoretical explanations of the effect of supplementary tutoring. Finally, I examine empirical literature on the effect of supplementary tutoring on students' academic achievement and identify selection bias as a key methodological issue to be addressed.

Shadow Education/Private Supplementary Tutoring

In examining the issue of supplementary tutoring, I review two relevant bodies of literature. Throughout the review, I clarify terminologies relevant to the study of supplementary tutoring and identify the focus of my study. One body of research focuses on shadow education or private tutoring; the other body of research focuses on out-of- school-time lessons or afterschool tutoring organized by the school. Although these two bodies of studies are rooted in different research traditions and have a slightly different focus, both are relevant in defining the subject of my study. In one of the earlier studies (Stevenson & Baker, 1992), *shadow education* was defined as a set of out-of-school educational activities designed to enhance students' formal school career. These activities include a set of undertakings ranging from commercial afterschool classes and private home tutors, to correspondence courses. Stevenson and Baker argued that the use of shadow education improved a student's chance of successfully moving through the allocation process in formal schooling.

Bray (1999) described private supplementary tutoring as a shadow education system, noting that "shadow" is used as a metaphor in the following sense:

> First, private supplementary tutoring only exists because the mainstream education exists; second, as the size and shape of the mainstream system change, so do the size and shape of supplementary tutoring; third, in almost all societies much more public attention focuses on the mainstream than on its shadow; and fourth, the features of the shadow system are much less distinct than those of the mainstream system (Bray, 1999, p. 17).

Baker and his colleagues (2001) further defined shadow education as "outside-school learning activities paralleling features of formal schooling used by students to increase their own educational opportunities", noting that it includes "organized, structured learning opportunities that take on school-like processes" (p. 2). Examples of shadow education include a range of activities such as correspondence courses, one-on- one private tutoring, examination preparatory courses, and full-scale preparatory examination schools. The authors suggested that shadow education occurs worldwide, and is particularly extensive in Japan, Hong Kong, Singapore, Taiwan, Korea, Greece, and Turkey.

While *shadow education* has gained in popularity as a term for this particular activity, *private tutoring (or private supplementary tutoring)* often signifies the same phenomenon. In *The Shadow education system: Private tutoring and its implications for planners*, Bray (1999) defined private tutoring as having the following three elements: 1) supplementation to mainstream schools, 2) privateness, and 3) academic subjects. Supplementation means that tutoring covers subjects already covered in school. Privateness means that tutoring is provided at private expense[2]. Academic subjects indicate that academic subjects are the main focus, whereas lessons in music, art, and sports are excluded. This definition has been widely used in subsequent international studies on private tutoring.

The terms *shadow education* and *private tutoring (or private supplementary tutoring)* are often used interchangeably (Bray, 1999, 2009; Ireson et al., 2005; Lee & Shouse, 2011). However, specific nuances held by each term are also recognized in the literature. For example, while private tutoring has an image of "one-on-one" tutoring of an individual, shadow education

[2] Therefore, the author explicitly focused on "tutoring provided by private entrepreneurs and individuals for profit-making purposes" (Bray, 1999, p. 20).

has an image of extra lessons that "shadow" teachings in the mainstream school system (Buchmann et al., 2010; Byun & Park, 2012)[3] .

One issue with such terminology is the lack of clear definition on the funding aspect of supplementary tutoring. Bray (2003, pp. 19–20) wrote that private supplementary tutoring focuses on tutoring provided by tutors for financial gain, and "it is not concerned with extra lessons that are given by mainstream teachers to needy pupils, on a voluntary basis, outside school hours." Following Bray's definition, private tutoring means that "tutoring is received on a fee-paying basis" (p. 20). This view does not necessarily hold for shadow education. Although private supplementary tutoring is widely called shadow education, whether shadow education simply refers to a fee-paying service or also includes free tutoring is not explicitly stated.

Despite such ambiguity in the definition, in many cases both *shadow education* and *private tutoring* tend to refer to supplementary tutoring that is market-driven and used on an individual basis. These types of tutoring often take place in private institutions or private homes of tutors and tutees, and are largely free from governmental control. As these lessons often require substantial fees that are outside poor families' available resources, they tend to create inequality between those who can afford such lessons and those who cannot. Thus, shadow education or private tutoring signifies a form of private education outside the formal education system that may not be available to all students.

Out-of-School-Time Lessons/Afterschool Tutoring

Another major body of research on supplementary tutoring is called out-of-school-time lessons or afterschool tutoring (e.g., Lauer et al., 2006; Weiss et al., 2009). These studies have mainly developed in the United States over the past decades. There has been a policy effort to provide quality afterschool programs for school-aged children under federal initiatives such as

[3] Some countries have a specific term for shadow education or private supplementary tutoring. This includes *juku* in Japan, *hagwon* in South Korea, *buxiban* in Taiwan, and *dersane* in Turkey.

the 21st Century Community Learning Centers (21st CCLC) program[4]. Unlike privately-funded supplementary tutoring, this type of tutoring is publicly funded. Therefore, it tends to serve low-achieving students (sometimes described as "at-risk" students) or families with fewer resources to allocate toward educational opportunities. These tutoring programs are provided for free or for a small fee. They are often held at school as a school-based program, or in the community as a community-based program.

Out-of-school-time lessons or afterschool tutoring is often considered a social service provided by the government or by non-profit institutions. These afterschool programs tend to have a wider purpose that is not limited to raising students' academic achievement. Rather, the range of purposes includes providing a safe environment for children, providing childcare for working mothers, and developing students' career and personality. However, among such purposes, academic achievement is gaining a greater focus in the recent U.S. policy climate to emphasize academic standards. As these tutoring programs are based on a policy initiative, a number of studies examining the quality and effect of tutoring have emerged in recent years. At the core of these evaluation studies is the desire to demonstrate the effectiveness of tutoring in supporting students' learning. By providing additional learning opportunities for students who need help, publicly-funded tutoring aims to close the achievement gap and reduce educational inequality between students.

"Afterschool program" as a broader term refers to a range of programs with a variety of content and goals. Hynes and Sanders (2010) raised two main purposes of afterschool programs that relate to social changes in the United States. One is *afterschool as childcare*. In response to the rise in maternal employment since the 1960s, a demand for non-maternal childcare increased, which paved the way for more afterschool programs. Afterschool programs that served as a type of childcare were also supported by a substantial increase in childcare funding since the mid-1990s. Another purpose is *afterschool as developmental and academic support*. This includes engaging youths in project-based learning, providing a safe afterschool environment, helping

[4] The 21st CCLC program was implemented in 1997 by the U.S. federal government to support academic achievement, provide enrichment opportunities, and reduce risky behaviors. Because the program focuses on achievement, students are enrolled regardless of mother's working status (Hynes & Sanders, 2010).

working mothers, and promoting career development for older youths. In addition, as schools face pressure to improve the academic performance of students who have social, emotional, and health issues, out-of-school time provides a suitable opportunity to support these students outside regular school hours (Hynes & Sanders, 2010).

Comparing Two Bodies of Research

To summarize, studies on shadow education/private tutoring usually examine supplementary tutoring provided by individuals or for-profit institutes and paid for by families. On the other hand, studies of out-of-school-time lessons/afterschool tutoring examine supplementary tutoring provided by schools or communities and funded by the government. Research on the former type of tutoring is conducted at the worldwide level, whereas research on the latter type of tutoring is conducted mostly in the United States. Table 2.1 offers a comparison of these two bodies of research.

Table 2.1 Comparison of the Two Bodies of Research

	Shadow Education/ Private tutoring	**Afterschool tutoring/ Out-of-school tutoring**
Funding	Families	Government
Nature	Private service	Social service
Provision	Corporate or individual	Government or non-profit
Place	Private centers or individual homes	School or community settings
Context	International	Mainly in the U.S.

Although these two lines of research have been pursued separately, the two streams should be considered together, as both types of tutoring exist in a single-country context even though one type may be more dominant than the other. For example, private tutoring exists in the United States (Buchmann, 2010; Byun & Park, 2012) despite the prevalence of afterschool tutoring. Similarly, afterschool tutoring exists in Japan despite the prevalence of private tutoring.

In fact, the border between private tutoring and afterschool tutoring/out-of-school tutoring is increasingly blurring. Not only do both types of tutoring share the characteristic of being an organized out-of-school activity that provides additional academic help for students, but policy intervention brings them together where privately-funded tutoring is increasingly integrated into public policies. This includes the situation in which private tutoring once used by wealthy students becomes available to poor students via public subsidies. The point is that one form of tutoring (tutoring paid for by families) may evolve into another form of tutoring (tutoring via public funding) as a result of policy changes. Conversely, the promotion of publicly-funded tutoring for poor families as a policy measure may encourage the development of privately-funded tutoring to be used by wealthy families.

For example, tutoring that used to be paid for by families could now be provided via public funding under the supplemental educational services mandate in the No Child Left Behind Act (NCLB) in the United States (Vergari 2007). Under this policy, school districts are required to provide supplementary tutoring to students in schools that failed to make adequate yearly progress (AYP) over three consecutive years. The policy aims to raise the academic achievement of lower-income and lower-achieving students by providing them publicly-funded free tutoring. In 2006–2007, 3.3 million students were eligible for Title I supplemental educational services, a six-fold increase since 2002–2003 (U.S. Department of Education, 2009).

Japan also has undertaken a publicly-funded tutoring initiative on the local level in recent years. Starting in 2005, several districts in Tokyo provided financial assistance for tutoring to low-income families on welfare who had elementary or middle school children. In 2008, the Tokyo prefectural government expanded the assistance to all eligible families and introduced a no-interest loan policy for financing private tutoring. The purpose of this policy was to encourage economically-disadvantaged students' entrance into high schools and colleges, thereby reducing inequality in educational opportunities (Tokyo Metropolitan Government, 2008).

South Korea's afterschool policy is another example of a mix of private tutoring and afterschool tutoring in a country (and also where privately-funded tutoring is being replaced by publicly-funded tutoring). After a series of attempts to reduce household spending on private tutoring, in 2005 the Korean government introduced an afterschool policy that aimed to offer high-quality tutoring programs at a low cost. A major goal of the policy was to narrow

educational gaps due to socioeconomic status by offering quality afterschool tutoring programs in school. The classes are sometimes taught by certified instructors from private tutoring institutions (Lee, 2005).

Factors that Affect Students' Participation in Supplementary Tutoring

Previous studies have examined several key factors that are associated with student participation in supplementary tutoring.

Academic achievement. Studies that reveal the association between students' academic achievement and participation in supplementary tutoring have shown two contrasting results. On the one hand, higher-achieving students are more likely to participate in supplementary tutoring in many East Asian societies (Bray & Kwok, 2003; Lee, 2005; Stevenson & Baker, 1992). Similarly in the United States, higher-achieving students are more likely to participate in a specific type of tutoring for college entrance preparation (Anderson, 2011; Buchmann et al., 2010).

On the other hand, lower-achieving students are more likely to participate in supplementary tutoring in certain contexts, especially through tutoring programs for lower-achieving students or students at risk in the United States (U.S. Department of Education, 2007; Weiss et al., 2009). This is primarily because the government subsidizes supplementary tutoring for students who need additional help, through initiatives such as the 21st Century Community Learning Centers (CCLC) and supplemental educational services mandate under the No Child Left Behind Act in the United States. Looking at this from an international perspective, Baker and his colleagues (2001) also found that supplementary tutoring was used as a remedial strategy by lower-achieving students in many countries, including the United States, Canada, Australia, and France.

Socioeconomic status. Studies have also examined the relationship between family's socioeconomic status and students' use of supplementary tutoring. The measure of socioeconomic status (SES) typically includes parental occupation, education, and income. Similarly to the relationship between academic achievement and tutoring participation, the positive relationship between students' SES and their use of tutoring is observed in many East Asian societies. Studies have revealed that students from higher-SES families are more likely to

participate in supplementary tutoring, especially that of a private nature (Bray & Kwok, 2003; Lee, 2005; Rohlen, 1980). Also in the United States, higher-SES students are more likely to participate in tutoring for college entrance preparation (Anderson, 2011; Buchmann et al., 2010; Byun & Park, 2012), although the percentage is relatively small compared to afterschool tutoring.

As mentioned above in the case of the United States, the negative relationship between students' SES and tutoring participation also has been observed. This typically occurs when tutoring is publicly subsidized for lower-SES students, where family's financial resources do not constrain students from participating in tutoring. Lower-SES students are eligible to participate in tutoring in educational systems in which this activity is publicly subsidized as a matter of government policy.

Parental involvement. Parental involvement is another major factor that may be related to students' participation in tutoring. Park et al. (2011) conceptualized tutoring as one of the strategies of parental involvement and revealed the positive relationship between parental involvement and the use of private supplementary tutoring. Students often receive supplementary tutoring in order to gain academic excellence and advantage outside school. Parents who encourage their children to engage in additional learning opportunities outside school hope that their children succeed in their regular school or on national examinations. In this regard, supplementary tutoring suggests the demand beyond formal schools. This is where parental involvement comes in. Some observers consider private supplementary tutoring as a market response to deficiencies in formal schooling, wherein families purchase extra lessons to compensate for such deficiencies (Dawson, 2010; Dierkes, 2008). Other scholars argued that parental anxiety has led families to pursue educational advantage outside school (Aurini & Davies, 2004; Judson, 2010; Smyth 2009), and that private supplementary tutoring is an activity through which parents can invest in their children's learning and thus enhance their educational achievement (Yamamoto and Brinton, 2010).

Socio-demographic characteristics. Other major student-level factors include students' grade level, gender, number of siblings, urbanicity, race/ethnicity, immigrant status, and educational motivation (Bray, 1999; Byun & Park, 2012; Dang, 2007; Park, 2012). Studies have suggested that students' participation in tutoring varies by students' grade level. For example, the third-year middle school students have the highest participation rates in tutoring in Japan, as the

majority of them prepare for high school entrance examination (Mori & Baker, 2010). Students' participation in tutoring may also vary by gender and the number of siblings, where norms about educational investment vary by these characteristics. Supplementary tutoring tends to be more prevalent in large cities, mainly because of the availability of tutoring. Race/ethnicity is another major factor that may affect participation in tutoring, especially in the United States. While Asian students are more likely to participate in tutoring in some context, such as for SAT preparation (Buchmann et al., 2010; Byun & Park, 2012), black and Hispanic students are more likely to participate in tutoring in other context, such as for school-based afterschool programs (U.S. Department of Education, 2007). These facts also relate to the discussion that immigrant background and religiosity influence students' participation in tutoring (Byun & Park, 2012; Park, 2012; Zhou & Kim, 2006). Park (2012) suggested that ethnic communities such as immigrant churches promote social capital, thereby affecting educational aspirations and expectations among families in the community. Finally, students' non-cognitive features including their motivation to study may also be related to participation in tutoring (Steinberg, 2011).

Theoretical Considerations on the Role and Impact of Supplementary Tutoring

Based on these findings from previous studies, two theoretical models on the role of supplementary tutoring are presented in Table 2.2. These models are the "social reproduction" and "social mobility" models. They show two hypothetical ways in which supplementary tutoring operates in different institutional contexts, showing two different directions of selection. Since these arguments are theoretically driven, the reality is often more complex than described in the models. For example, as mentioned above, supplementary tutoring in the United States is used by both higher-SES and lower-SES students.

In the social reproduction model, tutoring is voluntarily sought by families with the financial resources to pay for it. The main users are students from middle-class families and the nature of instruction is enrichment. The purpose of the tutoring is to gain academic excellence and advantage. The tutoring is considered a private service, so that families usually spend both financial and cultural resources in supporting their children to participate in supplementary tutoring. In terms of social stratification, this model is considered to reinforce existing inequality.

In the social mobility model, tutoring is publicly subsidized by the government. The main users are students from low-income families and the nature of instruction is remedial. The purpose of tutoring is to ensure minimum proficiency for students who need the most help. Tutoring is considered a social service or form of cultural resources that support low-SES children's learning. In terms of social stratification, this model is considered to reduce inequality and promote upward social mobility for low-status students.

Table 2.2 Two Theoretical Models of Supplementary Tutoring

	Social Reproduction Model	**Social Mobility Model**
Funding	Families (private)	Government (public)
Main users	Middle-class students	Lower-income students
Nature of instruction	Enrichment	Remedial
Purpose	Academic excellence	Minimum proficiency
Nature of service	Private service	Social service

Theoretically, three possible consequences exist on the effect of supplementary tutoring: positive effect, negative effect, and no effect. For each case, I suggest some theoretical explanations below. When supplementary tutoring has a *positive effect* on students' academic achievement, three factors may account for this positive effect: (1) additional learning time, (2) quality of tutoring, and (3) students' motivation and engagement. First, additional learning time increases the level and extent of subject materials learned by students and thereby increases their academic achievement (Aronson et al., 1998; Dobbie & Fryer, 2011; NCTL, 2010). This idea assumes that more time spent on learning leads to better achievement. Such an argument is often the basis of the extended school time debate in U.S. education policy, including evidence borrowed from other countries that require a longer school day (Patall et al., 2010). Second, a better quality of tutoring may enhance students' achievement. Although quality may be difficult to measure, it may be observed through instructors' teaching experiences, qualifications, program content, or the price of tutoring. Recent study suggests that tutoring provided by certified teachers and college graduates are more effective than tutoring provided by college students (Jones, 2015).

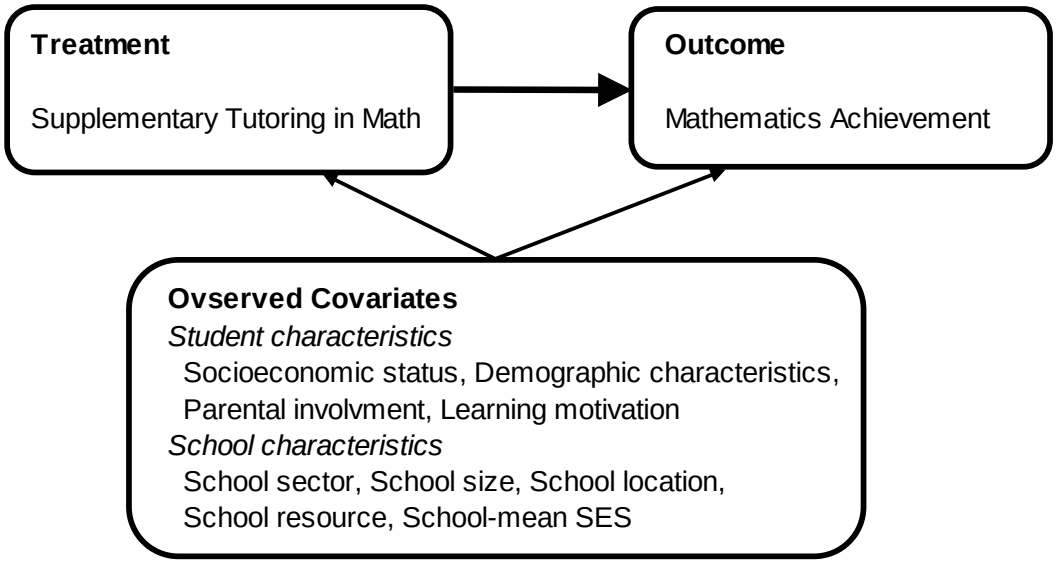
Anecdotal evidence from East Asian societies, including South Korea and Hong Kong, also indicates that the higher the quality of tutoring, the more expensive the service is—and students are expected to learn more from better-quality tutors. Third, tutoring may have an effect by enhancing students' motivation to study. Studies of student engagement suggest that more-involved students tend to learn better (e.g., Fredricks et al., 2004; Willms, 2003). Therefore, students may be expected to enhance their academic achievement by becoming more motivated to engage in and increasing their positive attitudes toward supplementary tutoring.

When supplementary tutoring has a *negative effect* on students' academic achievement, three factors may account for this negative effect: (1) lack of sufficient learning time, (2) low quality of tutoring (e.g., inexperienced instructors), and (3) lack of students' motivation and engagement (i.e., disengagement in learning). These are in fact the reversal of factors contributing to a positive effect explained above (additional learning time, quality of tutoring, and students' motivation and engagement). In addition, two additional factors for the negative effect may exist: (4) long hours of study (e.g., fatigue) and (5) discrepancy with formal school curriculum. This means that supplementary tutoring is no longer complementing but competing with formal schooling; not supplementing but simply repeating lessons in formal schools and not being effective or even having a negative influence.

When supplementary tutoring has *no effect* on students' academic achievement, two accounts may be possible. First, it is possible that these positive effects may be cancelled out when negative effects of supplementary tutoring are prevalent. That is, even when supplementary tutoring positively affects some students' academic outcomes, the "overall effect" may appear insignificant as some other students experience negative achievement gains, meaning the "heterogeneity" in the effect. Another scenario on the lack of effect is the successful removal of selection bias involved in students' participation in supplementary tutoring. For example, when a group of high-achieving students receive supplementary tutoring, a naïve analysis would suggest that supplementary tutoring has a positive effect on students' academic outcome. However, when characteristics that are originally associated with students' participation in tutoring (i.e., socioeconomic status, demographic characteristics) are adjusted, such seemingly positive effect of supplementary tutoring may disappear.

Figure 2.1 shows the conceptual model for my study.

Figure 2.1 Conceptual Model on the Effect of Supplementary Tutoring on Mathematics Achievement



Effect of Supplementary Tutoring on Students' Academic Achievement

Studies have revealed a range of impacts of supplementary tutoring on different dimensions of students' educational and social outcomes. In addition to the academic impact of tutoring on students' test scores, which is the main focus of this study, other key impacts of supplementary tutoring have been discussed in the literature. These include impact on college enrollment (Buchmann et al., 2010; Stevenson & Baker, 1992), on learning attitudes and engagement, on risk behaviors such as drug and alcohol use, and on personal and social development (Dynarski et al., 2004; Lauer et al., 2006; Patall et al., 2010; Weiss et al., 2009).

In this study, I focus on the effect of supplementary tutoring on students' academic achievement. The body of literature on the academic effects of tutoring has increased over the years. This increase is apparent in two ways, reflecting the previously-discussed frameworks in Table 2.1 and Table 2.2. One group of research studies assessed the degree of inequality created by the use of supplementary tutoring. These studies typically focused on shadow education or private tutoring, which is privately funded and used by students to increase their academic excellence. Another group of research studies more explicitly examined the extent to which

supplementary tutoring affects the achievement gap among students. This work emphasizes out-of-school-time lessons or afterschool tutoring that is publicly funded. In general, the former group of studies is rooted in the sociological literature while the latter is based in the program evaluation literature. Recognizing the difference in study purposes, I draw from both literatures in order to summarize the key findings of the impact of supplementary tutoring to date.

The Effect of Private Tutoring

Briggs (2001) analyzed the effect of commercial test preparation programs on the standardized college entrance examinations of U.S. high school students, using the National Education Longitudinal Survey (NELS) of 1988. Utilizing linear regression analysis and controlling for demographic variables, indicators of students' high school performance, as well as other covariates such as proxies for student motivation and dummy variables for other test preparation activities, Briggs found a statistically significant effect of coaching on two standardized test measures. According to Briggs, coaching had a positive effect on math and verbal sections of the SAT (Scholastic Aptitude Test), as well as on math and reading sections of the ACT (American College Testing). However, as the author noted, there is a chance that linear regression did not fully account for self-selection bias. That is, students who are more likely to seek coaching activities are more likely to be highly motivated students who have strong test-taking ability. As such, ability is unobservable but is a variable related to tutoring—Briggs cautioned that the statistical results may be biased due to failure to meet the conditional independence assumption in regression analysis.

Buchmann and colleagues (2010) also examined the effects of test preparation activities, which they called "American style" of shadow education, on the SAT and college enrollment. Drawing on the NELS data of 1994, the authors examined a series of test preparation activities (books/video/software, high school course, private course, private tutor) in an ordinary least squares (OLS) regression model. The key covariates in the model included family income, parental education, race/ethnicity, gender, residence, parental engagement, and prior achievement. The authors found a statistically significant effect of the test preparation services, especially for costly SAT courses and private tutoring. For example, compared to using no test preparation, taking a high-school course produced a gain in SAT scores of about 26 points. Similarly, taking a

private/commercial course increased scores by about 30 points; a private tutor increased scores by about 37 points.

While the study extended the literature on "shadow education" and contributed new insights from a U.S. perspective, methodologically it faced the same issue noted above—a lack of control for possible selection bias. Although the authors controlled major socio-demographic variables and prior achievement as key predictors of test preparation activities, students who receive some types of test preparation are likely to have better test scores and be from families with a higher income and more involved parents. Therefore, students who engage in test preparation have a different set of characteristics from students who do not engage in such preparation. Under these circumstances, it is difficult to determine whether score gains due to test preparation are attributable to the preparation itself or the fact that test preparation is utilized by different populations of students. In particular, students who engage in test preparation are considered to be highly motivated and better test-takers. In Buchman et al. (2010), these potential covariates are likely to be correlated with both measures for test preparation and the achievement outcome, leading to an endogenous problem. A regression model is less robust in handling endogeneity bias (Guo & Fraser, 2010), so their findings are likely to be upwardly biased if selection and endogeneity are issues.

Dang (2007) analyzed the Vietnam Living Standards Surveys 1997–1998 and 1992–1993 and found that spending on private tutoring has a positive effect on primary and lower secondary students' academic performance. The survey is a nationally representative household survey in Vietnam that contains information on student-level and school/community-level characteristics, as well as students' self-reported measure on academic performance in the previous grade (measured in four categories as excellent, good, average and poor). The study used the instrumental variable approach to address the possible endogeneity of household spending on private tutoring. As Dang suggested, although characteristics such as parental concern for children's education and student's innate ability are difficult to measure and observe, they are likely to affect both spending on private tutoring and students' achievement. He used private tutoring fees charged by schools as an instrument to represent the "official" price of private tutoring in the community and predict domestic spending on private tutoring.

Utilizing a joint Tobit and ordered probit econometric model, the analysis was conducted in two stages. First, the determinants of expenditures on private tutoring were estimated. Second, the impact of expenditures on private tutoring on student academic performance was assessed. The author included a range of variables to determine both expenditures on private tutoring classes and academic performance of students. Student characteristics included household expenditures per capita, students' grade level, age and age squared, gender, parental education, ethnic minority, and number of siblings. School and community characteristics included share of qualified teachers, number of book sets per student, share of people with higher educational degrees, and distance to school. Dang found that, controlling for other characteristics, private tutoring has a positive impact on students' academic performance, particularly for lower secondary students compared to primary students. However, the author cautioned that his argument depended heavily on the validity of the instrument used in the analysis.

Domingue and Briggs (2009) used data from the Education Longitudinal Survey of 2002 to estimate the effect of coaching on SAT score, using both linear regression and propensity score matching. They highlighted the advantage of using the propensity score matching approach in estimating causal effect compared to using the more traditional linear regression approach. In particular, propensity score matching restricted the sample to coached and uncoached students considered counterfactuals in estimating the effect. For those students who had taken both the PSAT and SAT, they found effect estimates of roughly 11 to 15 points on the math section and 6 to 9 points on the verbal, although only the math effects were statistically significant. They also found that coaching is more effective for certain kinds of students, particularly those who had taken challenging academic coursework and came from high-socioeconomic backgrounds.

Kuan (2011) used the Taiwan Educational Panel Study in 2001 and 2003 to look at the effects of private tutoring on mathematics performance among junior high school students in Taiwan. Via survey data for 7^{th}-grade students in 333 junior high schools in Taiwan, Kuan performed propensity score matching to address the selection issue in students' participation in cram schools. By matching tutored and non-tutored students who had similar probabilities of receiving tutoring, Kuan found a small average positive treatment effect of math cramming. With an additional analysis of the effect by student subgroups, the author found that the effect of math cramming was more prominent among each of the following subgroups: students with lower

probability of receiving cramming, students with lower prior math score, and students with lower parental educational level. Kuan recognized the issue of omitted variables as one limitation in his analysis, noting that propensity score matching itself cannot overcome the problem of unobservable measures.

Byun and Park (2012) employed the Educational Longitudinal Study to examine the effect of SAT and private one-on-one tutoring on high school students' mathematics and reading achievement. Using ordinary least squares (OLS) regression and controlling for prior achievement, they found a significant positive effect on supplementary tutoring for East Asian students.

Choi (2012) used the Seoul Educational Longitudinal Study to look at the effect of private tutoring on elementary, middle, and high school students' mathematics and English ability. Utilizing quantile regression, the authors found a heterogeneous impact of tutoring via distribution of students' achievement in math and English. The effect is larger for lower-achieving students, especially in English in elementary and middle school, and math in elementary and high school, suggesting that lower-achieving students may benefit more from tutoring in these cases. In particular, the author suggested that engaging in private tutoring in the English language confers greater advantage when students' grades are lower, since language skills are more malleable when students are younger.

The Effect of Afterschool Tutoring/Out-of-School Tutoring

Here, studies of the effect of supplementary, publicly funded tutoring are examined. These studies are all based on data from the United States due to the availability of high-quality U.S. data which enables program evaluation and to recent U.S. policy that calls for such evaluation studies. In fact federal and local governments have been encouraging the evaluation of supplementary tutoring programs to determine whether these programs are meeting their intended goals. Despite this call for evidence-based results and subsequent increase in such studies, empirical studies have offered mixed evidence. Using the National Longitudinal Study of NCLB (NLS-NCLB) and a difference-in-differences approach, researchers revealed statistically significant achievement gains among participants in supplementary tutoring in reading and math in the United States (U.S. Department of Education, 2007). The report was based on longitudinal

student-level data on nine large, urban school districts across the country. The NLS-NCLB survey originally sampled 300 school districts that included about 1,500 schools across the nation in 2004–2005 and 2006–2007.

These researchers noted that use of a conventional regression model to examine achievement effect cross-sectionally may produce biased estimates of program effects. To avoid this issue, they implemented a quasi-experimental difference-in-differences approach that uses within-subject pre-post comparisons and comparisons between participating and nonparticipating students. The method is also referred to as a student fixed-effect approach in econometric terms. By using this method and controlling for student characteristics (not explicitly mentioned in the report), they found positive achievement gains among participants in supplementary tutoring in reading and math. The study also revealed that those who participated in these programs for several years had twice the gains of students who participated for one year, and that African American, Hispanic, and students with disabilities experienced greater achievement gains from participation in tutoring activities.

Contrary to the above findings, some studies have shown a non-significant effect of tutoring. Using data from Jefferson County Public Schools in Kentucky, Munoz and Ross (2009) compared students who received tutoring with students who were eligible for tutoring but did not receive it, and who had similar characteristics based on the following five variables: previous diagnostic test scores in reading, gender, race, participation in the free or reduced-price lunch program, and single-parent homes. The Jefferson Country Public Schools are the 26th largest school district in the nation and located in a large metropolitan area. Of 150 schools in the district, 30 were required to offer the NCLB-mandated supplemental educational services during the 2005–2006 school year when the survey took place. Although students, parents, teachers and administrators were generally in favor of the program, Munoz and Ross found overall non-significant effects of tutoring for those who received tutoring, both in reading and mathematics, compared to the matched control students.

The study recognized the need to isolate confounding factors in measuring the impact of supplementary tutoring. It also referred to a range of uncontrollable factors, including "characteristics of the tutoring setting, contamination from core academic and other support programs, student interest and motivation, and limitations of standardized achievement tests for

sensitively measuring tutoring impacts" (Munoz & Ross, 2008, p. 3), all of which may bias the treatment effect. As the survey contained district-level data, specific description of the nature of supplementary tutoring was available:

> Providers serving students in Jefferson County, KY ranged from large national companies to local community-based organizations. A typical tutoring session lasted 1 hr after school, two days per week. Provider programs had a variety of methods of instruction. Some had one-on-one or small-group instruction; others tutored in the home of the student or online. Most programs lasted for several weeks, with the majority of tutoring taking place in the second (spring) semester of the school year (p. 6).

The study raised three possible explanations for the absence of tutoring effects. One is the limited duration of the tutoring activity relative to regular school programs and other educational experiences. Another is the failure of standardized tests to assess higher-order learning or specific knowledge skills that may be taught during tutoring sessions. The third is communication problems among parents, schools, and tutoring providers in implementing the program, including the lack of provider efforts to respond to parents' concerns.

Using regression discontinuity design, Jacob and Lefgren (2004) examined the effect of summer remedial programs on third- and sixth-grade students' academic achievement. They found that remedial programs had a modest but positive net impact on third-grade achievement in math and reading, but little net impact on sixth-grade achievement. This study used administrative data from the Chicago Public School system. Student-level information included test scores and student demographics (race, gender, age, guardian, and free lunch eligibility), bilingual and special education status, and residential and school mobility. School-level information included demographic and school resource information, such as racial and socioeconomic composition of the school.

Regression discontinuity method estimates the causal effect of an educational intervention by comparing the treated and controlled subjects who are just above or below the threshold of receiving the intervention. As students in this specific region are considered to have similar characteristics, students in the treated and control groups are considered to be randomly assigned.

The average treatment effect is therefore identified among marginal students around the threshold, as continuity of unobserved characteristics is assumed in that margin. In this case, the threshold is a certain level of test scores that indicates students' eligibility to receive remedial instruction.

Using survey data from Milwaukee Public Schools and the propensity score matching method, Heinrich, Meyer and Whitten (2010) found no statistically significant effect of supplementary tutoring on students' reading and math achievement gains at any grade level. They included a range of socio-demographic variables and prior achievement measures considered to affect current achievement. However, no effect was found. Heinrich and her colleagues (2010) supplemented this analysis with findings from a qualitative study and found that the lack of an effect may be due to several factors: insufficient hours attending supplementary tutoring, lack of continuity in students' daytime and after-school learning environments, quality of instruction, and student motivation to learn from tutoring.

To summarize, many studies focusing on privately-funded supplementary tutoring, reviewed in the first half of the above section, indicated a positive effect of engaging in this activity. On the other hand, studies focusing on publicly-funded supplementary tutoring in the United States, reviewed in the latter half of the section, offered mixed results[5] on the effectiveness of supplementary tutoring. Looking at this disagreement in measured program effects, Lauer et al. (2006) suggested possible heterogeneity in the effect of tutoring. The authors synthesized 35 studies of out-of-school-time programs that provided adequate control or comparison groups in examining treatment effects. Their summary suggested that some of a program's demonstrated ineffectiveness might be due to the aggregation of intervention outcomes that fail to differentiate heterogeneous effects according to student subgroups. Referring to the evaluation of 21st Century Community Learning Centers conducted by Dynarski et al. (2004), Lauer and her colleagues argued that aggregating results across programs can mask positive outcomes.

[5] Such disagreement in the effects of tutoring is potentially problematic in the U.S. where some types of tutoring are publicly funded and expected to have a program effect. In cases where tutoring is privately pursued by families, providers are not legally required to demonstrate program effects, even though families may be concerned about the effectiveness of tutoring as consumers of such services.

The above review also found that selection bias is a major problem in examining the effect of supplementary tutoring on academic achievement. Since the decision to receive supplementary tutoring is hardly randomized across students and their families, use of a quasi-experimental design is necessary to avoid estimation bias. Students may be selected for tutoring due to unobserved characteristics, such as motivation and test-taking skills. Studies that attempted to address the selection issue tackled the problem by including an instrumental variable or adding a large number of relevant covariates into the model, including a proxy measure for unobservable characteristics.

After controlling for selection bias, prior research tended to indicate an effect for a full population. Studies usually assume the homogeneity of the impact of supplementary tutoring, to obtain an average treatment effect across a general pool of students. However, several studies found the heterogeneity of the causal effect. The impact may differ according to social group—therefore, the effect of supplementary tutoring should be considered in specific contexts in which important social differences exist across student groups. One such feature includes students' grade levels. Since the studies summarized here focused on different grade levels, findings may only be interpreted within the particular grade level analyzed. Other key subgroup differences may include differences by students' probability of receiving tutoring, students' prior achievement, and parental education (Kuan, 2011). In addition, in the U.S. context, possible differences in the effect of supplementary tutoring according to race and ethnicity have been examined (Buchmann et al., 2010; Byun & Park, 2012; U.S. Department of Education, 2007). These findings suggest that tutoring effects may vary depending on contexts. Heterogeneity of the effect is important, since who benefits from and gains educational advantages from engaging in tutoring programs is a key issue relating to theoretical concerns about educational opportunity and equality.

Chapter 3
RESEARCH METHODOLOGY

This chapter states the research questions and describes the data and measures for the study. Propensity score matching is introduced as an analytic strategy.

Research Questions

Based on the reviewed literature, I ask the following questions: (1) What are the factors that affect students' participation in supplementary tutoring in the United States and Japan? (2) What are the effects of supplementary tutoring on students' mathematics achievement in the two countries? (3) Do the effects differ by student subgroups in each country?

Data and Measures

I used the 2006 Program for International Student Assessment (PISA) for this research. This is a cross-national study of achievement of 15-year-old students across the world. The study has been sponsored by the Organization for Economic Cooperation and Development (OECD) every three years since 2000. Administered to a minimum of 4,500 students in over 57 countries and economies across the world, PISA offers researchers internationally comparable home and school background information besides its performance indicators in reading, mathematics, and science. At the school level, PISA samples include approximately 150 schools (35 students from each school) from each country. The majority of the samples for 15-year-old students are equivalent to tenth graders in the United States, and first year high school students in Japan.

These students' mathematics achievement is my outcome variable. Mathematics is a common subject necessitating tutoring, and math performance is considered most comparable across countries because it is relatively unaffected by a country's language or culture. PISA accesses all three domains of reading, mathematics, and science every three years. Its objective is not limited to assessing the mastery of the school curriculum, but that of the knowledge and skills, which are essential for full participation in society (OECD 2005). Among the participating

countries in PISA, the mean of academic achievement is set to 500 and the standard deviation is set to 100.

My treatment variable is the supplementary tutoring in mathematics. In PISA 2006, student respondents were asked whether they spent time studying mathematics during out-of-school-time lessons, either at school, home or elsewhere (Q31). However, the nature of supplementary tutoring covered with this question was somewhat vague, as it did not specifically distinguish where the tutoring took place and who taught students. In order to identify the specific nature of tutoring, I have used auxiliary information that queries whether the students' own schoolteachers were involved in offering tutoring lessons (Q32). Details about these items that come from the PISA 2006 student questionnaire are shown in the Appendix A.

By considering these two items (Q31 and Q32) together, four categories were created: (a) receiving supplementary tutoring by teachers outside school (hereafter "out-of-school tutoring"), (b) receiving supplementary tutoring by schoolteachers themselves (hereafter "school tutoring"), (c) receiving both types of tutoring (hereafter "both tutoring"), and (d) receiving neither type of tutoring (hereafter "no tutoring")[6].

Students who received supplementary tutoring were likely to differ in critical ways from students who did not receive assistance. Thus, building on the previous studies, I included controls to account for selection bias that may exist in the choice of supplementary tutoring. These control variables included a range of student and school characteristics, which have been described below:

Highest parental occupational status was a continuous measure of the higher index of the occupational status of either parent. Originally, it entailed students' fathers and mothers being asked open ended questions about their occupations. The responses were coded into four-digit ISCO codes (ILO 1990) and then, mapped to the International Socio-Economic Index of occupational status (ISEI) (Ganzeboom et al., 1992). *Highest educational level of parents* had

[6] These categories distinguish the types of instructors for tutoring (schoolteachers or non-schoolteachers). Non-schoolteachers refer to tutors who are not associated with the concerned schools but teach elsewhere, including at other schools, home, commercial institutions or community organizations. Location of tutoring remains unspecified, which may be a limitation of PISA 2006.

six categories of the higher index of educational level of either parent. Parental education here was classified using the International Standard Classification of Education (ISCED) (OECD, 1999). Indices on parental education were constructed by recoding educational qualifications into the following categories: (0) None; (1) ISCED 1 (primary education); (2) ISCED 2 (lower secondary); (3) ISCED Level 3B or 3C (vocational/pre-vocational upper secondary); (4) ISCED 3A (upper secondary) and/or ISCED 4 (non-tertiary post-secondary); (5) ISCED 5B (vocational tertiary); and (6) ISCED 5A, 6 (theoretically oriented tertiary and post-graduate). *Wealth* was an index composed of seven items: (a) own room, (b) dishwasher, (c) Internet, (d) cell phone, (e) television, (f) computers, and (g) cars. *Home educational resources* was an index composed of the following five items: (a) a desk for study, (b) a quiet place to study, (c) educational software, (d) books for schoolwork, and (e) a dictionary.

Private-funded schools distinguished between publicly- or privately-funded educational institutions. The original index on school type had three categories: (a) public schools controlled and managed by a public education authority or agency, (b) government-dependent private schools controlled by a non-government organization or with a governing board not selected by a government agency, but which received more than 50% of their core funding from government agencies, and (c) government-independent private schools controlled by a non-government organization or having a governing board not selected by a government agency, but which received less than 50% of their core funding from government agencies. In my research, I combined (a) and (b) to create a measure for publicly-funded schools. The remaining (c) denotes a measure privately-funded schools[7].

Gender was measured as a dichotomous variable (female=1, male=0). The following four demographic characteristics were only measured for the United States. *Race/ethnicity* was a set of five dummy variables: (a) non-Hispanic white (reference), (b) black, (c) Hispanic, (d) Asian, and (e) other race. *Language at home* was a dichotomous variable: speaking foreign language at home (=1) and speaking native language at home (=0). *Grade level* was a set of three dummy variables: (a) modal grade (reference), (b) above modal grade, and (c) below modal grade.

[7] While it is also possible to distinguish privately-administered schools, I focus on the funding aspect as I consider it to be more relevant in students' selection into supplementary tutoring.

Mother's employment status was a set of three dummy variables: (a) mother works full-time, (b) mother works part-time, and (c) mother does not work (reference).

General interest in learning science was an index of instrumental motivation to learn science, constructed by the OECD. Positive values indicated higher levels of motivation. *Regular lessons in mathematics* was the students' self-reported measure on the hours spent taking math lessons at school. It had five categories: (a) none, (b) less than 2 hours, (c) 2 to 4 hours, (d) 4 to 6 hours, and (e) 6 hours or more. *Self study in math* was the students' self-reported measure about the hours spent on self study in math. It had the same five categories for the hours spent taking math lessons.

Science achievement was a continuous measure of science test scores and was included as a proxy of prior math achievement.

The following variables were included as covariates for school characteristics. *School mean parental education* was an aggregate measure of parental education at the school level. *School location* was a set of four dummy variables: (a) school in the village or small town (reference), (b) school in the town, (c) school in the city, and (d) school in a large city. *Shortage of math teachers* was derived from four items measuring the school principals' perceptions of factors hindering instruction at school. Higher values indicated a higher degree of teacher shortage. *Parent pressure on academic standards* was derived from three items measuring the degree of parental pressure on academic standards at their children's schools. Higher values indicated a higher degree of parental pressure. *School size* was the total enrolment at school based on enrolment data provided by the school principals. *Student-teacher ratio* was obtained by dividing the school size by the total number of teachers. *Quality of educational resources* was computed on the basis of seven items measuring the school principals' perceptions of potential factors hindering instruction at school. Higher values indicated higher levels of educational resources. *Percent receiving free/reduced lunch* was a continuous measure limited to the United States. *Vocational orientation* was a dichotomous measure limited to Japan.

Table 3.1 shows the variables used in this study.

Table 3.1 Variables for the Study

Description of Variables	*Original Variable Name*	*Construction of Variables*	
Outcome Variable			
Mathematics achievement	PV1MATH	Ranges from 173.15 to 808.763	
Treatment Variable			
Out-of-school tutoring in math	ST31Q05, ST32Q01-06	1=tutored, 0=not tutored	
School-tutoring in math	ST31Q05, ST32Q01-06	1=tutored, 0=not tutored	
Student Characteristics			
Private-funded school	schtype	1=private, 0=public	
Female	ST04Q01	1=female, 0=male	
Highest parental occupational status	hisei	Ranges from 16 to 90	
Highest educational level of parents	hisced	0=None, 1=ISCED 1, 2=ISCED 2, 3=ISCED 3B/C, 4=ISCED 3A/4, 5=ISCED 5B, 6=ISCED 5A/6	
Wealth	wealth	Scale score	
Home educational resources	hedres	Scale score	
General interest in learning science	intscie	Scale score	
Regular lessons in math	ST31Q04	Ranges from 0 to 7 in hours	
Self study in math	ST31Q06	Ranges from 0 to 7 in hours	
Science achievement	PV1SCIE	Ranges from 82.934 to 830.965	
Mother's employment status			
Mother full-time	ST05N01	1=mother working full-time, 0=otherwise	U.S. only
Mother part-time	ST05N01	1=mother working part-time, 0=otherwise	U.S. only
Mother does not work (Ref)	ST05N01		U.S. only

Race			
Non-Hispanic white (Ref)	race		U.S. only
Black	race	1=Black, 0=otherwise	U.S. only
Hispanic	race	1=Hispanic, 0=otherwise	U.S. only
Asian	race	1=Asian, 0=otherwise	U.S. only
Other race	race	1=other race, 0=otherwise	U.S. only
Language at home	ST12Q01	1=language of test, 0=other language	U.S. only
Grade level			
Modal grade (Ref)	ST01Q01		U.S. only
Above modal grade	ST01Q01	1=above modal grade, 0=otherwise	U.S. only
Below modal grade	ST01Q01	1=below modal grade, 0=otherwise	U.S. only
School Characteristics			
School mean parental education	hisced	Scale score	
School location			
School in village or small town (Ref)	SC07Q01	1=small town, 0=otherwise	
School in town	SC07Q01	1=town, 0=otherwise	
School in city	SC07Q01	1=city, 0=otherwise	
School in large city	SC07Q01	1=large city, 0=otherwise	
Shortage of math teachers	SC14Q02	1=not at all, 2=very little, 3=to some extent, 4=a lot	
Parent pressure on academic standards	SC16Q01	1=largely absent, 2=minority of parents, 3=many parents	
School size	schsize	Ranges from 3 to 10000	
Student-teacher ratio	stratio	Scale score	
Quality of educational resources	scmatedu	Scale score	
% receiving free/reduced lunch	SC05N01	Ranges from 0 to 100	U.S. only
Vocational orientation	iscedo	1=vocational, 0=general	Japan only

Counterfactual Analysis for Causal Inference

In examining my research questions on the causal effect of supplementary tutoring, I drew on the counterfactual approach (Holland, 1986; Rubin, 1974; Winship & Morgan, 1999). The key assumption of this approach, also called the potential outcomes framework, is to consider that subjects assigned to treatment and control groups have potential outcomes in both states (Winship & Morgan, 1999). When a subject is assigned to a treatment group, the potential outcome for the control state exists besides its actual treatment outcome. When a subject is assigned to a control group, the potential outcome for the treatment state exists besides its actual controlled outcome. This means that we consider two potential outcomes per subject, one for what actually happened and the other for what *would have happened* had the subject been assigned to the opposite state. The causal effect is defined as the difference in potential outcomes between the treatment and control states (Winship & Morgan, 1999).

In reality, one cannot observe *both* of these outcomes for the same subject at one time. When a subject receives a treatment, we can only observe its outcome for the treated state. The potential outcome for the controlled state will be left unobserved. Similarly, when a subject is under a control, the potential outcome for the treated condition will be unobserved. This issue is called the *fundamental problem of causal inference* in statistical research (Holland 1986). Often in natural science research, randomized controlled experiments may be conducted to simulate these two counterfactual states. Such randomized experiments are considered gold standards of scientific research for drawing causal inferences. However, often in social science research involving human participants and their social behaviors, randomized controls are neither feasible nor ethical. In such cases, researchers need to apply a quasi-experimental design to draw causal inferences by using existing survey data.

To estimate causal effects using the counterfactual approach, it is necessary to simulate two counterfactual outcomes that are unobserved in survey data. Following the notation by Morgan and Winship (2007), I denote potential outcome variables as Y^1 and Y^0. They correspond to two alternative causal states, one of which is unobserved for each subject in the data: Y^1 is an outcome for the state when a subject receives a treatment and Y^0 is an outcome for the state when a subject is under a control. In addition, I define causal exposure vis equal to 1

when a subject is actually exposed to the treatment and 0 when a subject is unexposed to the treatment.

Table 3.2 shows a framework for counterfactual inference. Two of the unobserved (or counterfactual) outcomes are highlighted in the table. One is an outcome for the hypothetical state when a subject would have received a treatment, when it was actually under a control ($Y^1 \mid D=0$). Another is an outcome for the hypothetical state when a subject would have been under a control, when it was actually treated ($Y^0 \mid D=1$).

Table 3.2 A Framework for Counterfactual Inference

Group	Y^1	Y^0
Treatment group (D=1)	Observable as Y	Counterfactual
Control group (D=0)	Counterfactual	Observable as Y

(From Morgan & Winship, 2007, p. 35)

In the above table, causal effects are defined within rows by comparing the outcomes between Y^1 and Y^0. Since we cannot observe counterfactual outcomes for the same individual *i*, we estimate causal effects by aggregating the individual outcomes. The Average Treatment Effect (ATE) is the difference in means between the two potential outcomes, denoted as follows:

$$ATE = E(Y^1 - Y^0)$$
$$= E(Y^1) - E(Y^0)$$

The Average Treatment effect on the Treated (ATT) is a specific condition of ATE when the treatment effect is considered only for those who have been treated. This outcome is substantially more meaningful when a researcher is interested in the group of students who are typically exposed to the treatment state.

$$ATT = E(Y^1 - Y^0 \mid D=1)$$
$$= E(Y^1 \mid D=1) - (Y^0 \mid D=1)$$

The Average Treatment effect on the Untreated (ATU) is another specific condition of ATE when the treatment effect is considered only for those who are untreated. This outcome may be substantially more meaningful, for instance, when a researcher wishes to know the effect of expanding a certain treatment (i.e., job training program) to the population that is currently not receiving the treatment.

$$ATU = E(Y^1 - Y^0 \mid D=0)$$
$$= E(Y^1 \mid D=0) - (Y^0 \mid D=0)$$

Propensity Score Methods

As one way to draw a causal inference, propensity score methods were developed in statistics and these have subsequently been used in many research fields including economics, medicine, and education. According to a seminal study by Rosenbaum and Rubin (1983), the propensity scores are defined as a conditional probability of assignment to treatment given the observed covariates. These are a type of balancing score that are predicted with covariates and summarized into a single-dimensional scale. Usually, logit or probit models are used to generate these propensity scores. After prediction, each person is assigned a propensity score, regardless of whether he or she actually received the treatment. While propensity scores originally take the form of probabilities, the logit of the probability is often used in the matching process due to its distributional properties. The propensity scores are estimated using the following logit equation:

$$\ln \frac{\Pr(T=1 \mid X)}{1 - \Pr(T=1 \mid X)} = \alpha + \beta X$$

The propensity of receiving a treatment is calculated as follows:

$$\Pr(T=1 \mid X) = \frac{\exp(\alpha + \beta X)}{1 + \exp(\alpha + \beta X)}$$

Where α is the estimated constant term; β is the estimated vector of coefficients; and X is the vector of covariates (Dehejia & Wahba, 2002; Rosenbaum & Rubin, 1983).

Propensity score analysis has an important assumption called the strongly ignorable treatment assignment. This means that the assignment for a treatment condition does not depend on the outcome of interest. Essentially, this is based on the same idea as the conditional independence assumption in the ordinary least squares (OLS) regression. When this assumption

is satisfied, the method mimics randomization. However, when the assumption is not satisfied, the results may be biased.

Propensity scores are a means to an end. As propensity scores signify one's likelihood of receiving treatment, they enable a matching of the units with similar likelihoods of receiving treatments. It is through this matching process that we know the effects of the treatment. Since propensity scores are on a continuous scale, matching units based on the exact same score is impossible. Therefore, we match units based on a similar range of propensity score distribution[8].

Advantages of Propensity Score Methods

There are some advantages of using propensity scores in making causal inferences. First, since propensity scores are one-dimensional balancing scores, matching units based on a multiple dimensions of covariates becomes feasible. Second, since propensity score analysis is a semi-parametric method, it is more suitable for drawing causal inferences than the OLS model. The OLS model is potentially problematic when there are few counterfactual groups with a similar tendency to receive treatment. In such cases, the parametric assumption of the OLS model relies on extrapolation, which does not come from the actual data. In order to reduce this potential bias, the propensity score analysis ensures that there is a substantial overlap between the comparable counterfactual groups, which is called the "common support" region. This process eliminates those treated subjects with no comparable controls. Third, unlike some quasi-experimental methods that rely on the longitudinal design of data, propensity score methods do not necessarily require such a data structure. When correctly applied, the propensity score analysis is applicable to cross-sectional data when making causal inference (e.g., Dronkers & Avram, 2010; Leow et al., 2004; Vandenberghe & Robin, 2004).

Applications of Propensity Score Methods

For my specific research question, propensity score methods enabled an examination of the causal effect of supplementary tutoring on students' academic achievement, by comparing the

[8] Rosenbaum and Rubin (1983) suggested that there were three major ways to enable such comparison: matching, sub-classification, and covariate adjustment.

achievement outcomes of the tutored (treated) students with the non-tutored (controlled) students who, in all other ways, had nearly identical background characteristics. Therefore, students who received supplementary tutoring were matched with students who did not receive supplementary tutoring but had a similar propensity score.

The propensity score analysis was conducted as follows. First, I used a logistic regression to estimate the probability of students' receiving a treatment. The selection of predictors that were included in the propensity score equation ultimately determined the accuracy of the propensity score results (Caliendo & Kopeinig, 2008). This first step answered my first research question; who participated in supplementary tutoring. Second, using the predicted probabilities from the logistic regression, I matched students in the treatment and non-treatment groups based on their estimated propensity scores. After verifying the covariate balance, I estimated the Average Treatment effect on the Treated (ATT) in terms of mathematics achievement, which indicated the differences in potential achievement between the tutored and the non-tutored students given the propensity scores. This second step answered my second research question; whether participation in tutoring had any causal effects. Subsequently, the propensity score analysis was conducted separately for student subgroups of interest. This third step answered my third research question; whether the effects of tutoring differ by student subgroups.

In this study, I investigated two treatments: "out-of-school school" supplementary tutoring and "school" supplementary tutoring. In order to sort out the effects for each type of treatment, I made two comparisons: (a) students who have received out-of-school tutoring (but not school tutoring) with students who received no tutoring, and (b) students who received school tutoring (but not out-of-school tutoring) with students who received no tutoring.

I used the logit model to predict students' probability of receiving supplementary tutoring. The predictor variables were selected based on the previous empirical and theoretical literature on students' participation in tutoring, as well as how well these variables predicted their participation in my model. After obtaining the propensity scores, I checked how the propensity scores balanced between the treated and the control groups. I used two sample t-tests to make sure that the mean for each covariate did not significantly differ between the two groups.

In addition to checking the covariate balance, I compared the distribution of the propensity scores between the tutored and non-tutored students using a histogram. Some students were predicted to have a higher propensity to receiving tutoring, irrespective of whether they actually received tutoring or not. Some students were predicted to have a lower propensity to receiving tutoring, irrespective of whether they received tutoring or not. The purpose of this comparison was to match students with similar likelihoods of receiving tutoring. In order to ensure that the comparison was made within the reasonably similar propensity score range, I imposed common support, which was to remove either treated cases (tutored students) or control cases (non-tutored students) whose propensity scores did not fall between the minimum and maximum propensity scores of either cases were removed from the sample. Following these procedures ensured that the outliers that could potentially bias the results were excluded from the analysis, and that data was balanced.

Subsequently, I matched students using three different matching techniques and compared the results across these methods. Each matching technique had its own strengths. The first matching technique was the *nearest-neighbor* method. This was a case where the control group was matched to a treated case based on the closest propensity score. The idea behind this method was to match students who were similar in terms of their propensity score distance. I used an option to impose a tolerance level on the maximum propensity score distance (caliper distance) to avoid the risk of bad matches. According to the suggestion by the existent literature, I set this caliper to a quarter of the standard deviation of a propensity score distribution (Guo & Fraser, 2010). I chose a one-to-one matching with the replacement of control units (Dehejia & Wahba, 2002).

The second matching technique was the *stratification* method. This method divided propensity scores into a set of strata and matched treatment and control cases within each stratum. This was based on the idea of matching the treated and controlled observations within strata that had similar propensity score ranges. After the difference in mean outcomes was calculated for each stratum, the weighted average of the difference across all the strata was obtained by considering the number of cases in each stratum.

The third matching technique was the *kernel* matching. Kernel matching used weighted averages of all cases in the control group to estimate the counterfactual outcomes. The

weight was calculated using the propensity score distance between a treated case and matched controlled cases, with the Epanechnikov kernel. This method matched every available pair between the treated and control groups as it weighed the differences in outcomes according to their distance. A closer pair gained more weight and had more influence on the result, whereas a distant pair gained less weight and had less influence on the result.

In addition to estimating the average treatment effect with propensity score methods, I also ran the OLS models to obtain the comparable estimates of the effects of supplementary tutoring on students' achievement. I used the same set of variables used to predict propensity scores in my OLS models. By comparing the estimated treatment effects across propensity score methods and an OLS model, I discussed how my results were robust depending on the estimation strategies.

Finally, to examine my third research question; whether the effect of supplementary tutoring varied by student sub-groups, I divided the sample and estimated the treatment effects separately for each group, using the three matching methods mentioned above. Through this process, I examined whether there existed some heterogeneity in the causal effects.

In estimating a causal model for academic achievement, a major limitation of the cross-sectional databases such as the PISA came to the fore. This was that they lacked repeated measures of achievement. However, propensity score modeling seemed to be the best possible method to estimate the causal effect under such circumstances (Dronkers & Robert, 2008; Rutkowski & Rutkowski, 2010). I used the science test scores as a proxy for previous achievement in mathematics[9]. I checked sensitivity by estimating the ATTs with and without science achievement being mentioned in the logit model to predict the propensity scores.

Missing Data

To deal with missing data, I implemented the stochastic regression imputation, a type of single imputation method that estimates the missing values based on the predicted values generated by a regression model plus a residual term to reflect uncertainty in the predicted values (Little & Rubin, 2002). Compared to multiple imputation in which estimates are calculated from multiple datasets, single imputation only creates one dataset, often yielding underestimated

[9] Reading test scores are absent for the United States in 2006 due to technical issues.

variances. Using the Stata's "ice" command, I used all variables in the analysis model as well as some auxiliary variables that are not in the analysis model but are highly correlated with analyzed variables that have missing information. The imputation was conducted by running a series of regression equations predicting the value for each individual missing value, using the remaining covariate information (Little & Rubin, 2002). This means that each variable in the imputation model served as both predictor and response variables.

In the current data for the United States and Japan, there was no missing data for mathematics achievement, the dependent variable. For the treatment variables on the types of supplementary tutoring, 4.58% were missing in the U.S. and 1.51% were missing in Japan. For other covariates, those with higher than 5% of missing information included the following variables: in the United States, 6.95% were missing for highest parental occupational status, 10.41% for school size, 17.29% for student-teacher ratio, and 7.08% for percentage of students receiving free/reduced lunch. In Japan, 8.38% were missing for highest parental occupational status.

Chapter 4
EMPIRICAL RESULTS

In this chapter, I examine the causal effect of two types of supplementary tutoring—out-of-school and school—on students' mathematics achievement, using propensity score matching. For the United States and Japan, I first show frequencies of participation in out-of-school tutoring and describe differences between tutored and non-tutored students in terms of student and school characteristics. I then match samples using propensity scores and check covariate balances between treated and control groups. As I obtain matched samples, I estimate the causal effect of tutoring participation on students' mathematics achievement. I also examine the heterogeneity of the causal effect in terms of some student characteristics.

Participation in Supplementary Tutoring

Table 4.1 shows summary statistics for students' tutoring status in the United States. Among all U.S. students in the sample, 6.2% received out-of-school tutoring in math, 11.5% received school tutoring in math, 11.6% received both types of tutoring in math, and 70.7% received neither type of tutoring. Before controlling for any factors, students who received no tutoring had the highest average mathematics test score (488.51), followed by students who received out-of-school tutoring (475.02) and students who received school tutoring (458.93). Students who received both types of tutoring had the lowest achievement scores (411.82).

In order to analyze the results for out-of-school tutoring, I compared students who received out-of-school tutoring with students who received no tutoring. In this case, I excluded the group of students who received both types of tutoring and the group who received school tutoring. After implementing these restrictions, the sample size for the U.S. dropped from 5,611 to 4,312. To analyze the results for school tutoring, I compared students who received school tutoring with students who received no tutoring. In this case, I excluded the group of students who received both types of tutoring and the group who received out-of-school tutoring. After adding these restrictions, the sample size for the U.S. dropped from 5,611 to 4,612. Values in the table were calculated using single imputation.

Table 4.1 Summary Statistics of Students' Tutoring Status, United States

	Out-of-school tutoring	School tutoring	Both tutoring	No tutoring	Total
%	6.2	11.5	11.6	70.7	100.0
N	347	646	652	3966	5611
Math achievement	475.02	458.93	411.82	488.51	475.18
SD	(83.35)	(88.06)	(82.06)	(86.92)	(89.87)

Table 4.2 shows the summary statistics for students' tutoring status in Japan. Among all Japanese students in the sample, 8.2% received out-of-school tutoring in math, 11.9% received school tutoring in math, 6.0% received both types of tutoring in math, and 74.0% received neither type of tutoring. Before controlling for any factors, students who received out-of-school tutoring had the highest average mathematics test score (572.61) among all four categories. This was followed by students who received school tutoring (522.77) and students who received no tutoring (522.27), who had roughly the same average test scores. Students who received both types of tutoring had the lowest achievement scores (512.56).

In order to analyze the results for out-of-school tutoring, I compared students who received out-of-school tutoring and no tutoring. In doing so, the sample size dropped from 5,952 to 4,888. To analyze results for school tutoring, I compared students who received school tutoring and no tutoring. The result was a drop in sample size from 5,952 to 5,108. Values in the table were calculated using single imputation.

Table 4.2 Summary Statistics of Students' Tutoring Status, Japan

	Out-of-school tutoring	School tutoring	Both tutoring	No tutoring	Total
%	8.2	11.9	6.0	74.0	100.0
N	486	706	358	4402	5952
Math achievement	572.61	522.77	512.56	522.27	525.82
SD	(80.54)	(92.00)	(102.21)	(87.95)	(89.88)

Difference between Tutored and Non-tutored Students

The findings in Table 4.3 show that in the United States, students who received either type of tutoring differed on several student and school characteristics from students who received no tutoring. The table also contains the results of significance tests that showed whether tutored and non-tutored students significantly differed on each variable. I first interpret the findings for out-of-school tutoring and then those for school tutoring.

In the United States, students who received out-of-school tutoring in math tend to have lower math achievement. They are more likely to be in public schools and tend to be female. On average, tutored students are from the same socioeconomic level as non-tutored students in terms of parental occupational status, education level, and wealth. However, tutored students tend to have more home education resources compared to non-tutored students. In terms of academic motivation, tutored students in the U.S. have greater interest in learning science and study by themselves for more hours. Tutored students are more likely to have mothers who are employed. In terms of race, Black and Asian students are more likely to be tutored, whereas White students are less likely to be tutored. With regard to school characteristics, tutored students in the U.S. tend to be in schools with a lower level of mean parental education, but with slightly higher level of parental pressure on academic subjects. Their schools tend to be larger and located in a large city.

In the United States, students who received school tutoring in math tend to have lower academic achievement in math and science. They are more likely to be in public schools and tend to have a lower socioeconomic status in terms of parental occupation. However, tutored students have better home education resources than non-tutored students. In terms of academic motivation, tutored students in the U.S. have more interest in learning science and study longer by themselves. They tend to have lower math achievement compared to their school mean achievement. As for race, tutored students are more likely to be Black and Hispanic and less likely to be White. They are slightly less likely to speak non-native language at home and tend to be either above or below modal grade. For school characteristics, tutored students are in schools with lower level of mean parental education and higher level of students receiving free/reduced lunch. Their school size tends to be slightly larger and these schools tend to be located in large cities than in small town.

Table 4.3 Descriptive Statistics by Tutoring Status, United States

Variables	United States							
	Tutored (Out-of-school)			Tutored (School)			Not tutored	
	Mean	SD		Mean	SD		Mean	SD
Dependent Variable								
Mathematics achievement	475.02	83.35	**	458.93	88.06	**	488.51	86.92
Student Characteristics								
Private-funded school	0.07	0.26	*	0.08	0.27	*	0.11	0.31
Female	0.58	0.49	**	0.53	0.50		0.49	0.50
Highest parental occupational status	53.18	15.98		50.88	17.13	**	52.77	16.91
Highest educational level of parents	4.90	1.19		4.74	1.33		4.81	1.26
Wealth	-0.04	0.93		-0.02	0.99		0.03	1.01
Home educational resources	0.15	0.91	**	0.06	0.95	*	-0.02	1.01
General interest in learning science	0.21	0.89	**	0.17	0.86	**	-0.08	1.02
Regular lessons in math	4.51	2.94		4.27	2.93		4.33	3.10
Self study in math	2.80	0.96	**	2.71	0.98	**	2.34	0.96
Difference from school mean math achievement	2.33	69.00		-11.05	76.87	**	8.26	73.93
Science achievement	495.05	98.78		468.15	100.75	**	504.01	102.06
Mother's employment status								
Mother full-time	0.61	0.49		0.55	0.50		0.57	0.49
Mother part-time	0.17	0.38		0.15	0.36		0.15	0.35
Mother does not work (Ref)	0.20	0.40	*	0.26	0.44		0.25	0.44
Race								
Non-Hispanic white (Ref)	0.50	0.50	**	0.50	0.50	**	0.64	0.48

Black	0.16	0.37	**	0.17	0.38	**	0.10	0.31
Hispanic	0.18	0.39		0.24	0.43	**	0.16	0.37
Asian	0.07	0.26	**	0.05	0.21		0.03	0.18
Other race	0.07	0.25		0.04	0.20	+	0.06	0.23
Language at home	0.86	0.35	*	0.85	0.36	**	0.90	0.30
Grade level								
Modal grade (Ref)	0.71	0.45		0.66	0.47	**	0.74	0.44
Above modal grade	0.18	0.38		0.20	0.40	+	0.17	0.37
Below modal grade	0.11	0.31		0.14	0.35	**	0.09	0.29
School Characteristics								
School mean parental education	4.76	0.58	*	4.73	0.58	**	4.83	0.58
School location								
School in village or small town (Ref)	0.22	0.42	**	0.32	0.47	+	0.36	0.48
School in town	0.32	0.47		0.30	0.46		0.31	0.46
School in city	0.25	0.44		0.23	0.42		0.22	0.42
School in large city	0.17	0.38	**	0.12	0.33	**	0.09	0.28
Shortage of math teachers	3.30	0.90		3.30	0.94	+	3.36	0.89
Parent pressure on academic standards	2.30	0.65	*	2.13	0.69	**	2.22	0.67
School size	1570.99	1073.55	**	1401.60	941.38	+	1327.05	957.36
Student-teacher ratio	16.31	5.11	**	15.63	4.47		15.50	4.70
Quality of educational resources	0.32	0.95		0.31	0.99		0.32	1.00
% receiving free/reduced lunch	36.20	26.75	**	36.43	27.67	**	32.02	25.75
N	**347**			**646**			**3966**	

** p<0.01, * p<0.05, + p<0.1

Note: Statistical significance for each column shows a comparison with the non-tutored category.

Findings in Table 4.4 show that in Japan, students who received either type of tutoring differed in several student and school characteristics from students who received no tutoring. After interpreting findings for out-of-school tutoring, I interpret those for school tutoring.

In Japan, students who received out-of-school tutoring in math tend to have higher academic achievement in math and science than students who received no tutoring. They are more likely to be in private schools and their socioeconomic status tends to be higher than that of non-tutored students in terms of parent occupational status, education level, wealth, and home education resources. On average, tutored students in Japan have more interest in learning science and study by themselves for more hours. With regard to school characteristics, tutored students tend to be in schools with a higher level of mean parent education and higher level of parental pressure on academic subjects. Their schools tend to be larger and located in cities than in towns. These schools have better educational resources and are more academically than vocationally oriented.

In Japan, students who receive school tutoring in math tend to have the same level of academic achievement in math and science compared to students who are not tutored. Tutored students are more likely to be in private schools and tend to be male. On average, tutored students have higher socioeconomic status in terms of parent occupation, education, home education resources, and wealth. Tutored students in Japan tend to have greater interest in learning science and study longer by themselves. Their math achievement is slightly lower than their own school mean achievement. There is no significant difference in city size among schools that enroll tutored students. However, on average, tutored students are in slightly larger schools and experience greater parental pressure on academic subjects and better school resources.

Table 4.4 Descriptive Statistics by Tutoring Status, Japan

	Japan							
Variables	**Tutored (Out-of-school)**			**Tutored (School)**			**Not tutored**	
	Mean	SD		Mean	SD		Mean	SD
Dependent Variable								
Mathematics achievement	572.61	80.54	**	522.77	92.00		522.27	87.95
Student Characteristics								
Private-funded school	0.32	0.47	**	0.32	0.47	**	0.27	0.44

Female	0.51	0.50		0.47	0.50	*	0.51	0.50
Highest parental occupational status	55.56	15.12	**	50.86	15.03	*	49.42	14.45
Highest educational level of parents	5.53	0.84	**	4.97	1.09	*	4.87	1.14
Wealth	0.25	0.94	**	0.05	1.01	*	-0.05	0.99
Home educational resources	0.25	0.93	**	0.12	1.00	**	-0.06	0.99
General interest in learning science	0.19	0.94	**	0.16	0.90	**	-0.07	1.02
Regular lessons in math	6.18	1.77	**	5.35	2.36	**	4.86	2.38
Self study in math	2.61	0.99	**	2.38	0.91	**	1.99	0.89
Difference from school mean math achievement	-2.34	57.40		-2.21	63.22	+	2.03	60.09
Science achievement	581.93	86.07	**	532.94	100.35		530.21	97.24
School Characteristics								
School mean parental education	5.39	0.41	**	4.93	0.57		4.90	0.59
School location								
School in village or small town (Ref)	0.02	0.15	**	0.07	0.26		0.06	0.24
School in town	0.22	0.41	**	0.30	0.46		0.30	0.46
School in city	0.43	0.50		0.41	0.49		0.40	0.49
School in large city	0.33	0.47	**	0.22	0.41		0.24	0.43
Shortage of math teachers	3.81	0.49		3.83	0.46		3.80	0.51
Parent pressure on academic standards	2.61	0.57	**	2.36	0.64	**	2.24	0.65
School size	862.62	343.38	**	773.06	493.82	**	735.06	403.35
Student-teacher ratio	14.21	4.18	**	13.01	4.97	+	12.69	4.53
Quality of educational resources	0.65	1.06	**	0.53	1.02	**	0.37	1.01
Vocational orientation	0.04	0.19	**	0.21	0.41	**	0.28	0.45
N	**486**			**706**			**4402**	

** p<0.01, * p<0.05, + p<0.1

Note: Statistical significance for each column shows a comparison with the non-tutored category.

The above description reveals some similarities and differences in the ways students participate in two types of supplementary tutoring in two countries. For *out-of-school tutoring*, tutored students in the U.S. tend to exhibit lower academic achievement and the same level of socioeconomic status compared to non-tutored students. In contrast, tutored students in Japan tend to indicate greater academic achievement and higher socioeconomic status compared to non-tutored students. This contrast suggests that out-of-school tutoring is typically used for remedial purposes by average-SES students in the United States, whereas in Japan it is typically used for enrichment by higher-SES students who are already performing well. However, the two countries share similar trends on some measures, including home education resources, students' motivation to study, school location, and school size. This suggests that in both the U.S. and Japan, out-of-school tutoring is typically used by well-resourced and higher-motivated students who go to larger schools in large cities.

For *school tutoring*, tutored students in the U.S. tend to have lower academic achievement and lower socioeconomic status compared to non-tutored students. In contrast, tutored students in Japan tend to have the same level of academic achievement and higher socioeconomic status compared to non-tutored students. This contrast suggests that school tutoring is typically used for remedial purposes by lower-SES students in the United States, whereas it is typically used to maintain the existing performance level of higher-SES students in Japan. The two countries share similar trends in some measures, including home educational resources, students' motivation to study, and school size. This suggests that in both the U.S. and Japan, school tutoring is typically used by well-resourced and higher-motivated students who go to larger schools[10].

Estimating Propensity Scores

In order to estimate the causal effect of supplementary tutoring participation on students' math achievement, I estimated propensity scores for two types of tutoring in each country. Since propensity score analysis approximates a randomized experiment using survey data, students'

[10] Unlike out-of-school tutoring, school location is only relevant for the U.S. but not for Japan. That is, while school tutoring is typically used by students who live in large cities in the United States, students typically receive school tutoring regardless of their school location in Japan.

participation in two types of tutoring (out-of-school tutoring and school tutoring) are regarded as two types of treatment in my study. Based on previous studies, I chose a set of variables that simultaneously predict students' participation in each type of tutoring (treatment) and their mathematics achievement (outcome). I assumed that all of the predictors were observed prior to students' participation in tutoring, meaning that they were not affected by the treatment. In addition, I assumed that selection for participation in tutoring was solely based on observable characteristics included in the model. These conditions were necessary to estimate the causal effect of tutoring on mathematics achievement.

Using the predictor variables, I ran two sets of logit models for each country; one for out-of-school tutoring and the other for school tutoring, to estimate the probability of students' participation in tutoring. Here, the propensity score is defined as the predicted probability of students' assignment to, or participation in, supplementary tutoring (Rosenbaum & Rubin, 1983). Propensity scores are estimated to facilitate the comparison of outcomes between the treated (tutored) and control (non-tutored) subjects who are as similar as possible, in order to obtain less biased estimates of treatment effects based on observed characteristics. For a given propensity score, assignment to the treatment status is considered quasi-random; therefore, treated and control units should be on average observationally identical (Becker & Ichino, 2002). To achieve this condition, propensity scores as well as covariates need to balance between the treated and control groups. This process of checking the balancing property ensures that members of the treated and control groups are sufficiently similar (Becker & Ichino, 2002; Zeiser, 2011).

To create propensity scores and check balance, I used Stata's "pscore" command which executes the following procedures: (a) estimate the logit or probit model with all covariates; (b) split the sample into five or more strata of the propensity score; (c) within each stratum, test that the average propensity scores and means of each covariate do not differ between treated and control units; and (d) if the test fails in one stratum, split the stratum in half and test again (Becker & Ichino, 2002; Frisco et al,. 2007). The current analysis followed the above procedures in Stata and achieved balance in propensity scores and in most covariates between the treated and control cases within each stratum.

The results of these logit models are shown below. Table 4.5 shows the results for the United States. While the overall trends are similar to the results for the descriptive statistics in

Table 4.3, several features are worth noting. While two of the SES measures, parent education level and home education resources, marginally predict students' participation in out-of-school tutoring at the 10% level, SES measures that include these two are not significant predictors of school tutoring in the United States. This means that, controlling for other variables in the model, students who have more educated parents and students with more educational resources are more likely to receive out-of-school tutoring; however, students' likelihood of receiving school tutoring does not differ by these SES measures. When students' mothers are employed either full- or part-time (compared to no employment), students are more likely to participate in out-of-school tutoring. This does not apply to school tutoring, meaning that students participate in school tutoring regardless of mothers' employment status. In terms of race, Black and Asian students are more likely than White students to receive out-of-school tutoring. The case is slightly different for school tutoring, in which Black and Hispanic students are more likely than White students to receive tutoring.

Table 4.5 Logit Models on Students' Participation in Tutoring, United States

Variables	Out-of-school Tutoring	School Tutoring
Private-funded school	-.381	-.526 **
Female	.200 +	.004
Highest parental occupational status	.002	.000
Highest educational level of parents	.095 +	.049
Home educational resources	.125 +	.075
Wealth	-.092	.017
General interest in learning science	.235 **	.242 **
Regular lessons in math	.116	.281 **
Regular lessons in math, squared	-.018	-.039 **
Self study in math	1.276 **	1.179 **
Self study in math, squared	-.143 **	-.136 **
Science achievement	.001	-.003 **
Mother full-time	.296 *	-.049
Mother part-time	.461 **	.156
Black	.337 +	.444 **
Hispanic	.135	.494 **
Asian	.643 *	.379
Other race	.375	-.102

Language at home	-.021	-.011
Above modal grade	-.003	.241 *
Below modal grade	.246	.290 *
School mean parental education	-.268 +	-.018
School in town	.409 *	.194
School in city	.461 *	.226
School in large city	.765 **	.234
Shortage of math teachers	-.124 +	-.089 +
Parent pressure on academic standards	.183 +	-.211 **
School size	.000	.000
Student-teacher ratio	.004	-.008
Quality of educational resources	.019	.035
% receiving free/reduced lunch	.005	-.003
N	**4312**	**4612**
Psuedo R2	.079	.080

** p<0.01, * p<0.05, + p<0.1

Table 4.6 shows the results for Japan. While the overall trends are similar to the results for the descriptive statistics in Table 4.4, several features are worth noting. While three of the SES measures (parent occupation, education, and wealth) are significant predictors of out-of-school tutoring, all of these measures are not significant predictors of school tutoring in Japan. This suggests that, controlling for other variables in the model, higher-SES students are more likely to receive out-of-school tutoring; however, students' likelihood of receiving school tutoring does not vary by these SES measures. Home education resources is not a significant predictor of out-of-school tutoring, but for school tutoring, students with more home education resources are more likely to participate in such tutoring.

Table 4.6 Logit Models on Students' Participation in Tutoring, Japan

Variables	**Out-of-school Tutoring**	**School Tutoring**
Private-funded school	-.174	.296 **
Female	-.140	-.288 **
Highest parental occupational status	.009 **	.003
Highest educational level of parents	.191 **	.037
Home educational resources	.075	.114 **

Wealth	.168 **	.029
General interest in learning science	.052	.200 **
Regular lessons in math	-.294 +	-.251 **
Regular lessons in math, squared	.038 *	.035 **
Self study in math	.907 **	1.452 **
Self study in math, squared	-.106 **	-.194 **
Science achievement	.002 *	-.001 +
School mean parental education	.769 **	-.574 **
School in town	.043	-.153
School in city	.226	-.218
School in large city	.443	-.203
Shortage of math teachers	-.367 **	.035
Parent pressure on academic standards	.250 *	.155 +
School size	-.001 **	.000
Student-teacher ratio	.037 *	.004
Quality of educational resources	.160 **	.093 *
Vocational orientation	-.805 **	-.180
N	**4888**	**5108**
Psuedo R2	.164	.059

Once propensity scores were obtained and the balancing property was satisfied, I checked for a potential substantial overlap in propensity scores between the treated and control cases. This overlap, called the common support region, ensures that comparisons are made within the propensity score range where there are sufficient treated and control cases (Becker & Ichino, 2002; Caliendo & Kopeinig, 2008). Previous studies suggest several ways to check for this overlap. I conducted Minima and Maxima comparison, a straightforward way to delete all observations whose propensity score is smaller than the minimum and larger than the maximum in the opposite group (Caliendo & Kopeinig, 2008). That is, treated cases (tutored students) and control cases (non-tutored students) whose propensity scores did not fall between the minimum and maximum propensity scores for either case were removed from the sample.

One should be careful in imposing the common support restriction, as “high quality matches may be lost at the boundaries of the common support and the sample may be considerably reduced” (Becker & Ichino, 2002, p. 362). Therefore, next I show a summary of propensity scores before and after imposing the common support restriction, and examine proportions of cases removed for being outliers. In addition, I show the histogram or density

distribution of the propensity score in both groups after imposing the common support. Such visual inspection enables a data quality check and helps determine which matching algorithm may work better in subsequent matching. It should be noted that common support is particularly important for kernel matching, as the method matches all control cases with treated cases using weights. On the other hand, nearest-neighbor method itself handles the common problem well, as the method discards control cases that do not find adequate matches (Caliendo & Kopeinig 2008).

Table 4.7 shows the summary of propensity scores for out-of-school tutoring in the United States. It shows that tutored students have a higher mean propensity score than non-tutored students. Common support removed 1.03% of the sample for having no comparable match, all in the control group (37 cases with the lowest propensity scores and 5 cases with the highest propensity scores). As a result, the maximum propensity score was adjusted to .411 instead of .511 and the minimum propensity score was adjusted to .009 instead of .003. From here on, I restrict the sample for propensity score analysis to cases that are "on support," by deleting subjects that are off the common support region.

Table 4.7 Summary of Propensity Scores, *Out-of-school Tutoring*, United States

	Treated (Tutored)					Control (Non-tutored)					Total
Propensity scores	N	Mean	SD	Min	Max	N	Mean	SD	Min	Max	
All	347	.125	.074	.009	.411	3965	.077	.058	.003	.511	4312
Off support (1.03%)	0					42	(37 below minimum, 5 above maximum)				
On support	347	.125	.074	.009	.411	3923	.077	.057	.009	.395	4270

Figure 4.1 shows the propensity score distribution after imposing the common support restriction for out-of-school tutoring in the United States. The bars in the upper half show the density distribution for tutored (=treated) students, and the bars in the lower half show the distribution for non-tutored (=control) students. This propensity score histogram by treatment status is made using the Stata's "psgraph" command. Note that the histogram is not proportional to the actual sample sizes for treated and control cases, but is adjusted to represent each group with equal weights. For example, treated cases are much smaller (347) than the control cases (3926) as described in Table 4.7.

The figure shows that students who received tutoring are more likely to have higher values on propensity scores than students who did not receive tutoring. The unequal distribution of propensity scores between treated and control groups indicates that assignment to the treatment (out-of-school tutoring) is not random and that systematic differences exist between these two groups of students.

Figure 4.1 Propensity Score Distribution with Common Support, *Out-of-school Tutoring*, United States

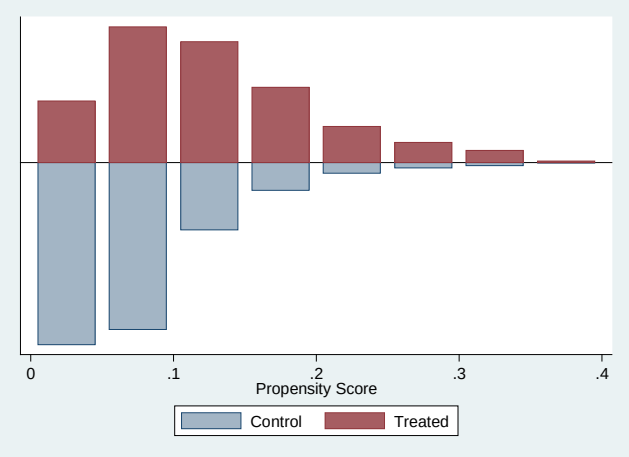


Table 4.8 shows a summary of propensity scores for school tutoring in the United States. Tutored students have higher mean propensity score than non-tutored students. Common support removed 0.74% of the sample for not having a comparable match, which were all in the control group (32 cases with the lowest propensity scores and 2 cases with the highest propensity scores). As a result, the maximum propensity score was adjusted to .630 and the minimum propensity score was adjusted to .020.

Table 4.8 Summary of Propensity Scores, *School Tutoring*, United States

	Treated (Tutored)					Control (Non-tutored)					Total
Propensity scores	N	Mean	SD	Min	Max	N	Mean	SD	Min	Max	
All	646	.200	.114	.020	.630	3966	.130	.085	.011	.730	4612
Off support (0.74%)	0					34	(32 below minimum, 2 above maximum)				
On support	646	.200	.114	.020	.630	3932	.131	.084	.020	.596	4578

Figure 4.2 exhibits propensity score distribution after imposing common support for school tutoring in the United States. The figure shows that students who received tutoring are slightly more likely to have higher values on propensity scores than students who did not receive tutoring, although the proportion of treated cases versus control cases is relatively similar across different propensity score ranges. The unequal distribution of propensity scores between treated and control groups indicates that assignment to the treatment (school tutoring) is not random and that systematic differences exist between these two groups of students.

Figure 4.2 Propensity Score Distribution with Common Support, *School Tutoring*, United States

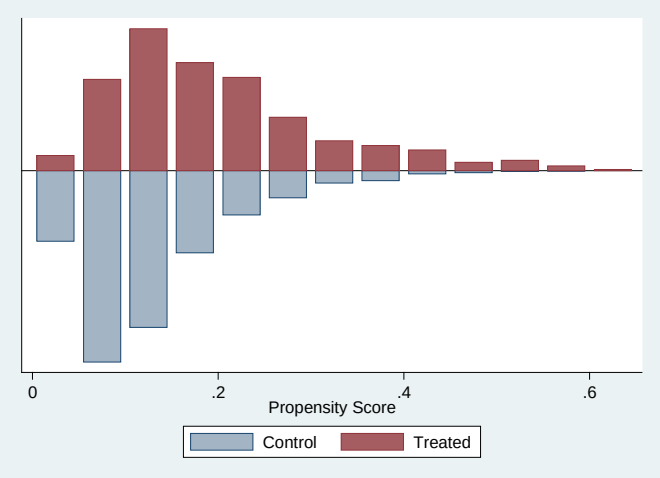


Table 4.9 offers a summary of propensity scores for out-of-school tutoring in Japan. It shows that tutored students have higher mean propensity scores than non-tutored students. Common support removed 11.03% of the sample for not having a comparable match, 2 of whom were in the treated group (with the highest propensity scores) and 536 in the control group (with the lowest propensity scores). As a result, the maximum propensity score was adjusted to .556 and the minimum to .008.

Table 4.9 Summary of Propensity Scores, *Out-of-school Tutoring*, Japan

	Treated (Tutored)					Control (Non-tutored)					Total
Propensity scores	N	Mean	SD	Min	Max	N	Mean	SD	Min	Max	N
All	486	.198	.113	.008	.584	4402	.089	.093	.001	.556	4888
Off support (11.03%)	2	(2 above maximum support)				536	(536 below minimum support)				
On support	484	.196	.111	.008	.553	3866	.100	.094	.008	.556	4350

Figure 4.3 indicates propensity score distribution after imposing common support for out-of-school tutoring in Japan. The figure shows that students who received tutoring are more likely to have higher values on propensity scores than students who did not receive tutoring. Students who did not receive tutoring tend to be clustered in the lowest propensity score range, suggesting that many of those who were predicted to be least likely to receive tutoring actually did not receive tutoring. The unequal distribution of propensity scores between treated and control groups indicates that assignment to the treatment (out-of-school tutoring) is not random and that systematic differences exist between these two groups of students.

Figure 4.3 Propensity Score Distribution with Common Support, *Out-of-school Tutoring*, Japan

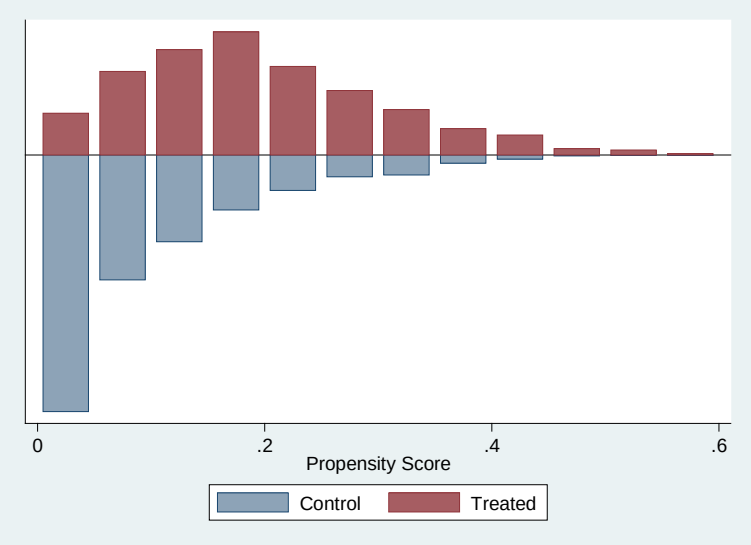


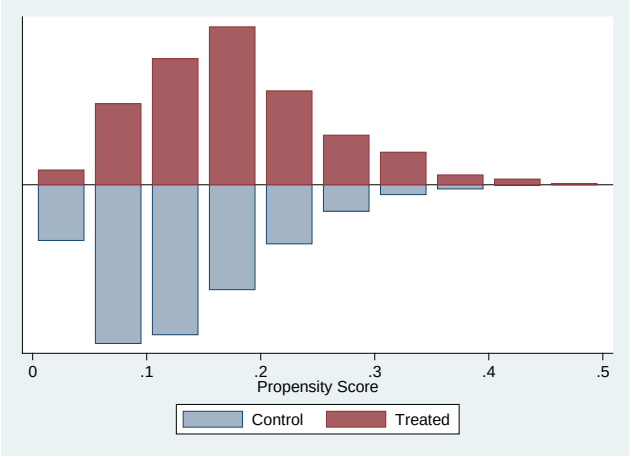
Table 4.10 offers a summary of propensity scores for school tutoring in Japan. It shows that tutored students have higher mean propensity scores than non-tutored students. Common support removed 1.81% of the sample for not having a comparable match, which were all in the control group (90 cases with the lowest propensity scores and 1 case with the highest propensity score). As a result, the maximum propensity score was adjusted to .466 and the minimum propensity score was adjusted to .030.

Table 4.10 Summary of Propensity Scores, *School Tutoring*, Japan

	Treated (Tutored)					Control (Non-tutored)					Total
Propensity scores	N	Mean	SD	Min	Max	N	Mean	SD	Min	Max	
All	706	.178	.079	.030	.466	4402	.132	.073	.017	.510	5108
Off support (1.81%)	0					91	(90 below minimum, 1 above maximum)				
On support	706	.178	.079	.030	.466	4311	.134	.072	.030	.462	5017

Figure 4.4 exhibits propensity score distribution after imposing common support for school tutoring in Japan. The figure shows that students who received tutoring are slightly more likely to have higher values on propensity scores than students who did not receive tutoring. The unequal distribution of propensity scores between treated and control groups indicates that assignment to the treatment (school tutoring) is not random and that systematic differences exist between these two groups of students.

Figure 4.4 Propensity Score Distribution with Common Support, *School Tutoring*, Japan



Matching Using Estimated Propensity Scores

Using propensity scores obtained from the logit models, I matched tutored (treated) and non-tutored (control) students who had a similar propensity of receiving two types of supplementary tutoring. The goal in performing matching was to produce two samples of students who were similar on all observed characteristics except for their participation in supplementary tutoring. I used three types of matching methods explained in the previous chapter: (a) nearest-neighbor matching (one-to-one match with replacement and within a caliper), (b) stratification matching, and (c) kernel matching.

As causal effects are estimated from counterfactual cases created from these matching methods, matching must be done appropriately. To show how well the matches were made, I checked the balance in propensity scores between treated and control cases. Balance in propensity scores was checked for the former two matching methods: nearest-neighbor matching and stratification method. Since the kernel method uses all the control cases with weights, it is hard to check balance in a meaningful way. Since nearest-neighbor and stratification methods are based on different ideas, I show how propensity scores balance in a different manner for each method. For the nearest-neighbor method, boxplots for propensity score distribution before and after matching are presented. For the stratification method, summary statistics for propensity scores for five strata after matching are presented.

Figure 4.5 shows the distribution of propensity scores for tutored (treated) and non-tutored (control) students before and after implementing nearest-neighbor matching, for out-of-school tutoring in the United States. The left figure, before matching, shows some overlap in propensity score distribution between the two groups . There are disparities at the highest end as well as around the mean values.

The right figure offers a distribution of propensity scores after matching for the same sample of students, using a nearest neighbor matching (one-to-one match with replacement and within a caliper). As a result of this matching, for out-of-school tutoring in the United States, the sample size decreased from 4,270 to 694 (347 treated and 347 controls). The figure shows that the distributions of propensity scores in two groups are well balanced. Control cases with relatively lower propensity scores are removed with matching, so that the mean and maximum values for the control cases rose after matching to achieve similar distributions between the two

groups. Substantively, this suggests that many of the students who were not tutored (control cases) also had a lower likelihood of receiving tutoring before matching; however, since those with a higher likelihood were selected for matching within in the control group, treated and control cases became more comparable.

Figure 4.5 Propensity Score Distribution before and after Matching (Nearest Neighbor), *Out-of-school Tutoring,* United States

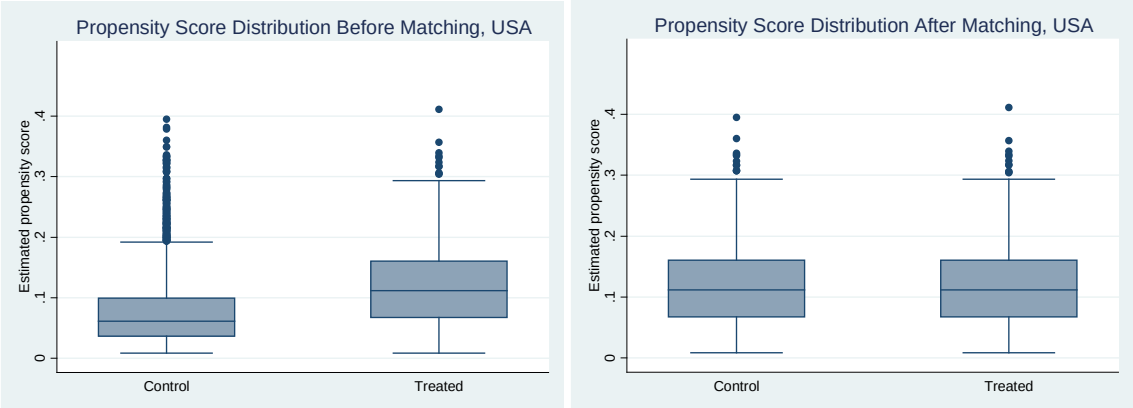


Table 4.11 offers summary statistics for propensity scores by five strata created via stratification matching for out-of-school tutoring in the United States. Unlike nearest-neighbor matching, in stratification matching sample size stayed the same as long as all treated and control cases fell under some strata and were used in matching. The table indicates that the means for propensity scores were similar between the treated and control groups within each stratum, demonstrating that each stratum was similar enough in terms of propensity scores.

Note that the fifth stratum only has one case in the treated group, with a propensity score of .411. This may suggest that even though common support was imposed, an outlier emerged when stratification matching was conducted. However, caution is necessary when deciding whether this particular case should be viewed as an outlier. As shown in Table 4.7, the next highest propensity score in the control group was .395, which is not hugely different from .411. The fifth stratum was created to ensure that the means in the treated and control cases in the fourth strata were similar enough. I kept this case in the fifth stratum because I believed that it would not significantly bias the result. Since the average treatment effect is obtained by

weighting the cases in each stratum, one case in the fifth stratum would not overly contribute to the overall estimate.

Table 4.11 Summary Statistics of Propensity Scores by Matched Strata (Stratification), *Out-of-school Tutoring*, United States

	Treated (Tutored)			Control (Non-tutored)		
	Mean	S.D.	N	Mean	S.D.	N
Stratum 1	**.035**	.011	47	**.031**	.011	1541
Stratum 2	**.074**	.014	101	**.072**	0.01	1413
Stratum 3	**.141**	.027	146	**.136**	0.03	806
Stratum 4	**.258**	.041	52	**.256**	0.04	163
Stratum 5	**.411**	.	1			0

Figure 4.6 shows the distribution of propensity scores for treated and control cases before and after implementing nearest-neighbor matching, for school tutoring in the United States. Before matching, the figure shows some overlap between students who received school tutoring (treated) and students who received no tutoring (controls), but also some disparities at the higher end as well as in their mean values. After matching, the figure shows that the distributions of propensity scores are similar in the two groups. This shows that within the control group, a smaller number of students with relatively high propensity scores was chosen through matching. As a result of nearest neighbor matching, for school tutoring in the United States, the sample size decreased from 4,578 to 1,292 (646 treated and 646 controls).

Figure 4.6 Propensity Score Distribution before and after Matching (Nearest Neighbor), *School Tutoring*, United States

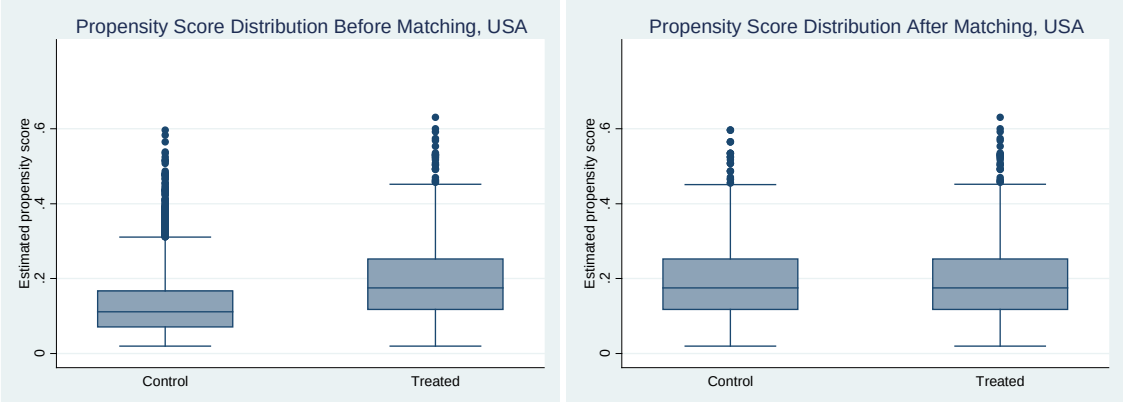


Table 4.12 offers summary statistics for propensity scores according to seven strata created by stratification matching for school tutoring in the United States. The table shows that the means for propensity scores were similar between treated and control groups within each stratum, indicating that each stratum was similar enough in terms of propensity scores.

Table 4.12 Summary Statistics of Propensity Scores by Matched Strata (Stratification), *School Tutoring*, United States

	Treated (Tutored)			Control (Non-tutored)		
	Mean	S.D.	N	Mean	S.D.	N
Stratum 1	**.041**	.008	16	**.038**	0.01	462
Stratum 2	**.079**	.013	98	**.075**	0.01	1249
Stratum 3	**.126**	.014	152	**.124**	0.01	1025
Stratum 4	**.175**	.014	116	**.173**	0.01	538
Stratum 5	**.271**	.054	216	**.266**	0.05	613
Stratum 6	**.473**	.054	47	**.464**	0.05	45
Stratum 7	**.630**	.	1			0

Figure 4.7 shows the distribution of propensity scores for treated and control cases before and after implementing nearest-neighbor matching, for out-of-school tutoring in Japan. *Before matching*, propensity scores were clustered in the lower tail in the control group. This suggests that students who were expected to have a lower probability of receiving out-of-school tutoring in Japan actually did not receive tutoring. *After matching*, the distribution is more balanced. As a result of nearest neighbor matching, for out-of-school tutoring in Japan the sample size decreased from 4,350 to 968 (484 treated and 484 controls).

Figure 4.7 Propensity Score Distribution before and after Matching (Nearest Neighbor), *Out-of-school Tutoring*, Japan

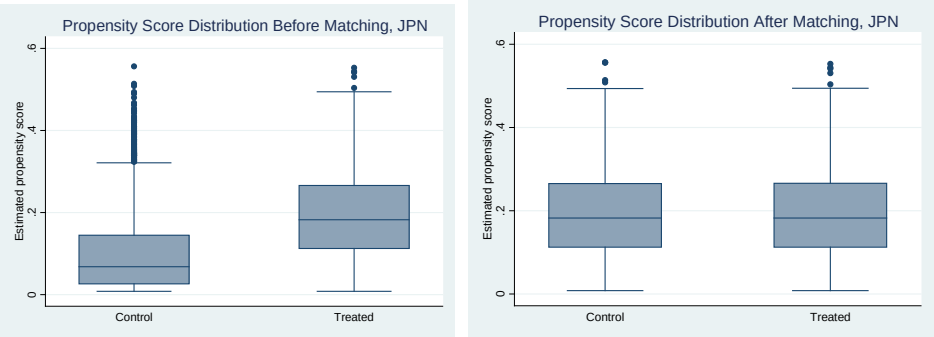


Table 4.13 exhibits summary statistics for propensity scores by seven strata created via stratification matching for out-of-school tutoring in Japan. The table shows that the means for propensity scores were similar between treated and control groups within each stratum, indicating that each stratum was similar enough in terms of propensity scores.

Table 4.13 Summary Statistics of Propensity Scores by Matched Strata (Stratification), *Out-of-school Tutoring*, Japan

	Treated (Tutored)			Control (Non-tutored)		
	Mean	S.D.	N	Mean	S.D.	N
Stratum 1	**.027**	.012	34	**.025**	.012	1617
Stratum 2	**.065**	.008	27	**.062**	.007	434
Stratum 3	**.088**	.007	39	**.087**	.007	353
Stratum 4	**.125**	.015	83	**.125**	.014	547
Stratum 5	**.176**	.014	97	**.174**	.014	347
Stratum 6	**.279**	.052	178	**.273**	.052	535
Stratum 7	**.458**	.045	26	**.441**	.037	33

Figure 4.8 shows the distribution of propensity scores for treated and control cases before and after implementing nearest-neighbor matching, for school tutoring in Japan. *Before matching*, the propensity scores tend to be concentrated in the lower ends of the control group. A*fter matching*, propensity score distributions are similar between the treated and control groups. As a result of nearest neighbor matching, for school tutoring in Japan the sample size decreases from 5,017 to 1,412 (706 treated and 706 controls).

Figure 4.8 Propensity Score Distribution before and after Matching (Nearest Neighbor), *School Tutoring*, Japan

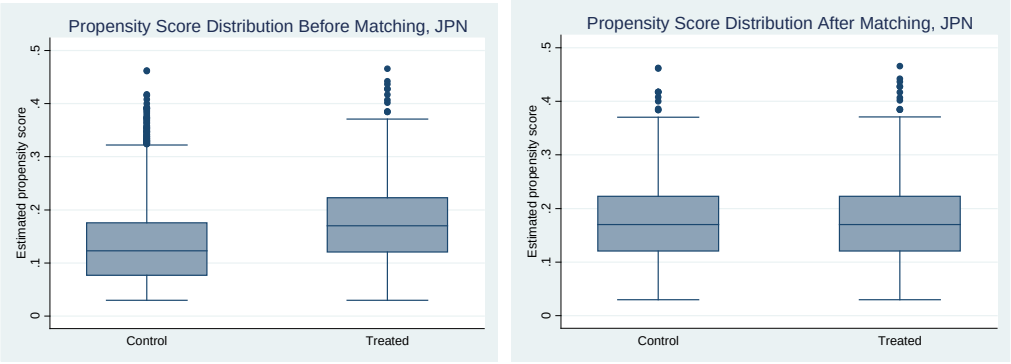


Table 4.14 shows summary statistics for propensity scores by eight strata created via stratification matching for school tutoring in Japan. The means of propensity scores were similar between treated and control groups within each stratum, showing that each stratum was similar enough in terms of propensity scores.

Table 4.14 Summary Statistics of Propensity Scores by Matched Strata (Stratification), *School Tutoring*, Japan

	Treated (Tutored)			Control (Non-tutored)		
	Mean	S.D.	N	Mean	S.D.	N
Stratum 1	**.041**	.006	18	**.041**	.006	423
Stratum 2	**.062**	.008	30	**.062**	.007	601
Stratum 3	**.088**	.007	70	**.087**	.007	598
Stratum 4	**.127**	.015	156	**.125**	.015	1134
Stratum 5	**.175**	.016	195	**.172**	.014	793
Stratum 6	**.241**	.028	177	**.237**	.027	648
Stratum 7	**.332**	.024	52	**.337**	.027	107
Stratum 8	**.428**	.020	8	**.426**	.025	7

Covariate Balance before and after Propensity Score Matching

As mentioned earlier, the current analysis used the Stata's "pscore" command to achieve balance between the treated and control cases within each stratum. During this process, the sample was split into five or more strata of the propensity score, and within each stratum, t-tests were made to ensure that means of each covariate did not differ between treated and control units. Since the same strata were used for the stratification method in the subsequent matching, this process tells whether covariate balance was achieved for the stratification method.

For out-of-school tutoring in the United States, all of the covariates in the propensity score model are balanced between treated and control cases within five strata. For school tutoring in the United States, all of the covariates are balanced with two exceptions: other race in the second stratum and home educational resources in the fifth stratum. For out-of-school tutoring in Japan, all of the covariates in the propensity score model are balanced between treated and control cases within seven strata. For school tutoring in Japan, all of the covariates are balanced

between treated and control cases within eight strata with one exception: interest in science in the second stratum.

I further checked covariate balance for nearest-neighbor method, by manually testing the treatment-control group differences in the means of each covariate, before and after matching. Nearest-neighbor method selects fewer control cases as opposed to stratification and kernel methods that use all available control cases. Therefore, I regarded that showing the covariate balance after this pair-matching process was particularly important in assessing the quality of the matches.

Table 4.15 shows the covariate balance before and after nearest-neighbor matching for out-of-school tutoring in the United States. It shows that while there are significant between-group differences in the mean of most covariates before matching, all of the significant differences are removed after matching. This contrast shows that covariates are successfully balanced after nearest-neighbor matching. The table also shows that the number of control cases significantly drops after matching.

Table 4.15 Covariate Balance before and after Matching (Nearest Neighbor), *Out-of-school Tutoring*, United States

	Before Matching				After Matching		
	Treated (N=347)	Control (N=3965)	t-test		Treated (N=346)	Control (N=346)	t-test
Private-funded school	.07	.11	2.00	*	.07	.06	-.77
Female	.58	.49	-3.05	**	.58	.61	.77
Highest parental occupational status	53.18	52.77	-.43		53.18	54.31	.92
Highest educational level of parents	4.90	4.81	-1.31		4.90	4.90	-.03
Home educational resources	.15	-.02	-3.00	**	.15	.10	-.73
Wealth	-.04	.03	1.15		-.04	-.06	-.26
General interest in learning science	.21	-.08	-5.18	**	.20	.20	-.09
Regular lessons in math	4.51	4.33	-1.06		4.50	4.71	.93
Self study in math	2.80	2.34	-8.59	**	2.79	2.81	.16

Science achievement	495.05	504.03	1.58		495.50	492.18	-.45
Mother full-time	.61	.57	-1.15		.60	.58	-.54
Mother part-time	.17	.15	-1.38		.17	.18	.20
Mother not working	.20	.25	2.04	*	.21	.21	.09
White	.50	.64	5.06	**	.50	.50	-.08
Black	.16	.10	-3.41	**	.16	.17	.10
Hispanic	.18	.16	-1.01		.18	.20	.39
Asian	.07	.03	-3.56	**	.07	.07	.00
Other race	.07	.06	-.85		.07	.07	-.15
Language at home	.86	.90	2.36	*	.86	.86	.00
Modal grade	.71	.74	1.20		.71	.72	.17
Above modal grade	.18	.17	-.51		.18	.15	-1.13
Below modal grade	.11	.09	-1.15		.11	.14	1.04
School mean parental education	4.76	4.83	2.01	*	4.76	4.77	.26
School in small town	.22	.36	5.17	**	.22	.25	.72
School in town	.32	.31	-.59		.32	.31	-.41
School in city	.25	.22	-1.38		.25	.25	.00
School in large city	.17	.08	-5.28		.17	.17	.20
Shortage of math teachers	3.30	3.36	1.27		3.30	3.32	.26
Parent pressure on academic standards	2.30	2.22	-2.00	*	2.29	2.26	-.63
School size	1570.99	1327.03	-4.51	**	1568.21	1490.12	-1.00
Student-teacher ratio	16.31	15.50	-3.05	**	16.31	16.17	-.36
Quality of educational resources	.32	.32	.06		.32	.37	.67
% receiving free/reduced lunch	36.20	32.00	-2.91	**	36.25	36.72	.22

** p<0.01, * p<0.05, + p<0.1

Table 4.16 shows the covariate balance before and after nearest-neighbor matching for school tutoring in the United States. It shows that all of the significant differences in covariate means are removed after matching, suggesting that covariates were successfully balanced after matching.

Table 4.16 Covariate Balance before and after Matching (Nearest Neighbor), *School Tutoring*, United States

	Before Matching				After Matching		
	Treated (N=646)	Control (N=3966)	t-test		Treated (N=646)	Control (N=646)	t-test
Private-funded school	.08	.11	2.12	*	.08	.08	.20
Female	.53	.49	-1.60		.53	.52	-.45
Highest parental occupational status	50.88	52.77	2.62	**	50.88	50.44	-.47
Highest educational level of parents	4.74	4.81	1.35		4.74	4.72	-.29
Home educational resources	.06	-.02	-1.90	+	.06	.10	.64
Wealth	-.02	.03	1.23		-.02	.04	1.07
General interest in learning science	.17	-.08	-5.92	**	.17	.18	.13
Regular lessons in math	4.27	4.33	.47		4.27	4.26	-.06
Self study in math	2.71	2.34	-9.13	**	2.71	2.69	-.29
Science achievement	468.15	504.01	8.29	**	468.15	468.61	.08
Mother full-time	.55	.57	1.13		.55	.58	.95
Mother part-time	.15	.15	-.52		.15	.15	.08
Mother not working	.26	.25	-.17		.26	.25	-.32
White	.50	.64	6.97	**	.50	.52	.87
Black	.17	.10	-4.99	**	.17	.16	-.52
Hispanic	.24	.16	-4.94	**	.24	.23	-.72
Asian	.05	.03	-1.54		.05	.05	.00
Other race	.04	.06	1.66	+	.04	.05	1.04
Language at home	.85	.90	3.86	**	.85	.88	1.64
Modal grade	.66	.74	4.19	**	.66	.64	-.70
Above modal grade	.20	.17	-1.70	+	.20	.17	-1.00
Below modal grade	.14	.09	-4.10	**	.14	.18	1.96
School mean parental education	4.73	4.83	3.76	**	4.73	4.74	.05
School in small town	.32	.36	1.84	+	.32	.31	-.48
School in town	.30	.31	.28		.30	.32	.72
School in city	.23	.22	-.61		.23	.22	-.60
School in large city	.12	.09	-3.17	**	.12	.12	.00
Shortage of math	3.30	3.36	1.66	+	3.30	3.27	-.60

teachers						
Parent pressure on academic standards	2.13	2.22	3.03 **	2.13	2.13	-.04
School size	1401.60	1327.05	-1.84 +	1401.60	1361.79	-.75
Student-teacher ratio	15.63	15.50	-.68	15.63	15.45	-.71
Quality of educational resources	.31	.32	.28	.31	.35	.73
% receiving free/reduced lunch	36.43	32.02	-3.99 **	36.43	37.10	.43

** p<0.01, * p<0.05, + p<0.1

Table 4.17 shows the covariate balance before and after nearest-neighbor matching for out-of-school tutoring in Japan. It shows that all of the significant differences in covariate means are removed after matching, suggesting that covariates were successfully balanced after matching.

Table 4.17 Covariate Balance before and after Matching (Nearest Neighbor), *Out-of-school Tutoring*, Japan

	Before Matching				After Matching		
	Treated (N=486)	Control (N=4402)	t-test		Treated (N=485)	Control (N=485)	t-test
Private-funded school	.32	.27	-2.62	**	.32	.32	-.28
Female	.51	.51	-.22		.51	.51	.00
Highest parental occupational status	55.56	49.42	-8.84	**	55.62	55.20	-.44
Highest educational level of parents	5.53	4.87	-12.39	**	5.53	5.58	.94
Home educational resources	.25	-.06	-6.51	**	.25	.26	.28
Wealth	.25	-.05	-6.34	**	.26	.27	.24
General interest in learning science	.19	-.07	-5.46	**	.20	.18	-.31
Regular lessons in math	6.18	4.86	-11.82	**	6.18	6.04	-1.24
Self study in math	2.61	1.99	-14.31	**	2.61	2.58	-.49
Science achievement	581.93	530.21	-11.25	**	582.34	578.30	-.75

School mean parental education	5.39	4.90	-17.86	**	5.39	5.39	-.13
School in small town	.02	.06	3.66	**	.02	.01	-.95
School in town	.22	.30	3.84	**	.22	.22	.08
School in city	.43	.40	-1.53		.43	.44	.32
School in large city	.33	.24	-4.32	**	.33	.32	-.14
Shortage of math teachers	3.81	3.80	-.55		3.81	3.79	-.49
Parent pressure on academic standards	2.61	2.24	-12.05	**	2.61	2.60	-.35
School size	862.62	735.06	-6.71	**	862.54	862.26	-.01
Student-teacher ratio	14.21	12.69	-7.09	**	14.21	14.49	1.06
Quality of educational resources	.65	.37	-5.94	**	.65	.67	.24
Vocational orientation	.04	.28	11.55	**	.04	.05	.95

** p<0.01, * p<0.05, + p<0.1

Table 4.16 shows the covariate balance before and after nearest-neighbor matching for school tutoring in Japan. It shows that all of the significant differences in covariate means are removed after matching, suggesting that covariates were successfully balanced after matching.

Table 4.18 Covariate Balance before and after Matching (Nearest Neighbor), *School Tutoring*, Japan

	Before Matching				After Matching		
	Treated (N=706)	Control (N=4402)	t-test		Treated (N=705)	Control (N=705)	t-test
Private-funded school	.32	.27	-2.92	**	.32	.32	.00
Female	.47	.51	2.02	*	.47	.47	.27
Highest parental occupational status	50.86	49.42	-2.44	*	50.88	51.43	.70
Highest educational level of parents	4.97	4.87	-2.15	*	4.97	4.99	.37
Home educational resources	.12	-.06	-4.42	**	.12	.09	-.53
Wealth	.05	-.05	-2.34	*	.05	.01	-.79

General interest in learning science	.16	-.07	-5.56	**	.16	.16	.11
Regular lessons in math	5.35	4.86	-5.02	**	5.35	5.25	-.77
Self study in math	2.38	1.99	-10.62	**	2.38	2.40	.38
Science achievement	532.94	530.21	-.69		533.10	538.08	.96
School mean parental education	4.93	4.90	-1.29		4.93	4.91	-.56
School in small town	.07	.06	-.68		.07	.06	-1.09
School in town	.30	.30	-.28		.30	.32	.52
School in city	.41	.40	-.49		.41	.37	-1.26
School in large city	.22	.24	1.26		.22	.25	1.51
Shortage of math teachers	3.83	3.80	-1.64		3.83	3.83	-.17
Parent pressure on academic standards	2.36	2.24	-4.45	**	2.36	2.34	-.72
School size	773.06	735.06	-2.25	*	773.27	776.46	.13
Student-teacher ratio	13.01	12.69	-1.70	+	13.01	13.04	.13
Quality of educational resources	.53	.37	-3.99	**	.53	.54	.14
Vocational orientation	.21	.28	3.68	**	.21	.20	-.59

** $p<0.01$, * $p<0.05$, + $p<0.1$

Causal Effect of Tutoring Participation on Students' Mathematics Achievement

Using the matched sample, I sought to determine whether students' participation in two types of tutoring had causal effects on mathematics achievement in the United States and Japan. Following procedures utilized to obtain average treatment effects on the treated (ATT) explained in chapter 3, ATTs were obtained by using nearest neighbor, stratification, and kernel matching as three alternative estimation methods. In addition, ATTs were obtained from the ordinary least squares (OLS) regression in order to compare results of the results of propensity score estimation

with the conventional estimation strategy. Detailed results for the OLS, including estimates for all other covariates, are presented and discussed in the Appendix B.

To ensure the sensitivity of these causal effect estimates on the inclusion and exclusion of science achievement as a covariate, which is used as a proxy for prior academic achievement, the same sets of analyses using with and without science achievement are repeated. Within each country, the result without science achievement is shown first, followed by the result with science achievement.

United States

Table 4.19 shows the estimates of the effect of out-of-school tutoring on math achievement in the United States, without science achievement included as a covariate. The ATT obtained using three methods – stratification, kernel, and OLS – are significantly negative and similar in size. Except for the nearest-neighbor estimates, the rest of the estimates all suggest that the average causal effect of out-of-school tutoring on math achievement in the United States is negative. That is, out-of-school tutoring has a detrimental impact on U.S. students' mathematics achievement.

Note that different numbers of control cases were used with the three matching methods. Since the nearest-neighbor method used one-to-one match, the same numbers of control and treated cases were used. Its sample size is about one-sixth of the sample size in the stratification and kernel methods. Compared with a large sample size, a small sample size tends to inflate the standard error, leading to a smaller t-statistic and insignificant coefficient. This very fact makes the nearest-neighbor method the most stringent test.

Table 4.19 Estimates of the Effect of *Out-of-school Tutoring* on Math Achievement, United States, *without* Science Achievement

	ATT/OLS	S.E.	t		N treat	N control	N total
Nearest neighbor	-7.130	6.831	-1.040		346	346	692
Stratification	-10.516	4.831	-2.177	*	346	3914	4260
Kernel	-10.178	4.852	-2.100	*	346	3922	4268
OLS	-11.699	4.015	-2.910	**			4312

Table 4.20 shows the effects of participation in out-of-school tutoring on math achievement in the United States, with science achievement included as a covariate. The effects from the OLS remain to be significantly negative. However, the ATT obtained utilizing nearest neighbor, stratification, and kernel are statistically insignificant, although their values are largely the same as the OLS. It is clear that propensity score methods are more likely to produce larger standard errors, thus removing statistical significance which is more likely to be found in the OLS method.

The inclusion of science achievement as a covariate changes both the propensity score estimates and OLS estimate into a consistently upward direction. When science achievement is included, the propensity score estimates suggest that out-of-school tutoring in the U.S. has no overall effect on math achievement, whereas the propensity score estimates indicated the negative effect when science achievement was excluded. However, OLS results consistently show the negative effect of out-of-school tutoring in the U.S., regardless of the inclusion of science achievement.

Table 4.20 Estimates of the Effect of *Out-of-school Tutoring* on Math Achievement, United States, *with* Science Achievement

	ATT/OLS	S.E.	t		N treat	N control	N total
Nearest neighbor	-2.540	6.681	-.380		347	347	694
Stratification	-5.776	4.804	-1.202		346	3924	4270
Kernel	-5.449	4.870	-1.120		346	3923	4269
OLS	-5.758	2.002	-2.880	**			4312

Table 4.21 exhibits the estimates of the effect of school tutoring on math achievement in the United States, without science achievement. Across propensity score methods and OLS method, all of the estimates are negative and statistically significant. This means that when science achievement is not used to predict students' participation in tutoring, it shows that the effect of school tutoring is negative in the United States. Compared to the estimates for out-of-school tutoring in the United States, the sizes of the effects for school tutoring are much larger in the negative direction.

Table 4.21 Estimates of the Effect of *School Tutoring* on Math Achievement, United States, United States, *without* Science Achievement

	ATT/OLS	S.E.	t		N treat	N control	N total
Nearest neighbor	-18.652	5.446	-3.420	**	644	644	1288
Stratification	-21.600	3.733	-5.786	**	645	3928	4573
Kernel	-20.639	3.895	-5.300	**	644	3940	4584
OLS	-21.450	3.327	-6.450	**			4612

After including science achievement (shown in Table 4.22), the ATTs for school tutoring in the United States obtained via all three propensity score methods are insignificant. Contrary to the estimates without science achievement, these results with science achievement show no overall effect of school tutoring on math achievement in the United States. The value of OLS estimate is relatively close the kernel estimates, going in the same negative direction. The OLS estimate is also statistically insignificant. All results suggest the lack of overall effect of school tutoring in the United States.

Table 4.22 Estimates of the Effect of *School Tutoring* on Math Achievement, United States, *with* Science Achievement

	ATT/OLS	S.E.	t	N treat	N control	N total
Nearest neighbor	-1.118	5.400	-.210	646	646	1292
Stratification	-4.561	3.339	-1.366	645	3933	4578
Kernel	-3.089	3.956	-.780	645	3932	4577
OLS	-2.491	1.582	-1.570			4612

Japan

Table 4.23 shows the estimates of the effect of out-of-school tutoring on math achievement in Japan, without science achievement. The ATT is consistently positive but statistically insignificant, suggesting that there is no overall effect of out-of-school tutoring in Japan. The effect OLS is also insignificant, supporting the lack of effect of out-of-schooling in Japan.

Table 4.23 Estimates of the Effect of *Out-of-school Tutoring* on Math Achievement, Japan, *without* Science Achievement

	ATT/OLS	S.E.	t	N treat	N control	N total
Nearest neighbor	1.873	4.603	.407	486	486	972
Stratification	.461	3.655	.126	486	3828	4314
Kernel	.267	4.219	.060	486	3869	4355
OLS	2.547	3.620	.700			4888

After controlling for science achievement, shown in Table 4.24, the ATTs obtained from the propensity score methods are consistently around the value of zero, and all results are statistically insignificant. The OLS estimate is also statistically insignificant. Thus, the OLS and propensity score methods, with or without science achievement, are consistent in showing null effects for out-of-school tutoring in Japan. Unlike previous results for the United States, the out-of-school tutoring results for Japan are not sensitive to the inclusion of science achievement.

Table 4.24 Estimates of the Effect of *Out-of-school Tutoring* on Math Achievement, Japan, *with* Science Achievement

	ATT/OLS	S.E.	t	N treat	N control	N total
Nearest neighbor	.601	5.595	.110	484	484	968
Stratification	.491	3.628	.135	484	3866	4350
Kernel	-.070	4.217	-.020	483	3866	4349
OLS	1.103	2.335	.472			4888

Table 4.25 exhibits the estimates of the effect of school tutoring on math achievement in Japan, without science achievement. It shows that, except for the nearest-neighbor method, all of the estimates are significantly negative, suggesting a detrimental effect of out-of-school tutoring on mathematics achievement in Japan.

Table 4.25 Estimates of the Effect of *School Tutoring* on Math Achievement, Japan, *without* Science Achievement

	ATT/OLS	S.E.	t		N treat	N control	N total
Nearest neighbor	-7.441	5.101	-1.460		704	704	1408
Stratification	-11.600	3.675	-3.157	**	704	4309	5013

Kernel	-12.244	3.820	-3.200	**	704	4316	5020
OLS	-11.967	3.752	-3.190	**			5108

Table 4.26 exhibits the effects of participation in school tutoring on math achievement in Japan, with science achievement. The ATTs obtained via all propensity score methods are consistently negative. However, the ATT using nearest-neighbor method is significant, whereas the ATTs using stratification and kernel methods are insignificant. The OLS estimate shows only marginally significant effect.

Table 4.26 Estimates of the Effect of *School Tutoring* on Math Achievement, Japan, *with* Science Achievement

	ATT/OLS	S.E.	t		N treat	N control	N total
Nearest neighbor	-12.171	5.309	-2.290	*	706	706	1412
Stratification	-4.541	3.866	-1.170		706	4311	5017
Kernel	-4.772	3.767	-1.267		704	4311	5015
OLS	-4.029	2.208	-1.820	+			5108

To summarize, these results generally indicate either negative or the lack of an overall effect of participation in two types of tutoring on math achievement in these two countries. When science achievement was included, none of the propensity score estimates except for the nearest-neighbor estimate in Japan showed any significant effect of tutoring. When science achievement was included, OLS estimate showed statistically significant negative effect for out-of-school tutoring in the United States and marginally significant negative effect for school tutoring in Japan. In general, when science achievement was included as an additional covariate, the negative estimates were upwardly adjusted and the positive estimates were downwardly adjusted. The statistical significance for these estimates after including science achievement tended to disappear or become weaker.

Heterogeneity of the Causal Effect of Tutoring Participation

These results indicated the lack of an overall effect of participation in either type of tutoring on math achievement in these two countries. However, these overall results may be masking subgroup differences. Using the nearest neighbor, stratification, and kernel methods, I

examined the heterogeneous effects of tutoring participation on math achievement according to several student characteristics.

First, heterogeneity by propensity score quintile was reviewed to determine whether those with greater or less likelihood of participating in tutoring gained more from attending the lessons. Previous studies on supplemental tutoring in Taiwan suggested that private math tutoring is more useful to those who are less likely to undertake it (Kuan, 2011). Therefore, heterogeneity in the causal effect was tested by propensity score quintile for both types of tutoring in each country.

Second, heterogeneity was examined by parent education level. Previous studies have suggested that private supplementary tutoring in the U.S. is more effective for students from high socioeconomic backgrounds (Domingue & Briggs, 2009), whereas supplementary tutoring that is publicly funded is more effective for at-risk students in the United States (Lauer et al., 2006). In my study, heterogeneity was tested by whether parent education level was above college or below high school.

Third, heterogeneity was examined by the extent of home education resources. A study in Korea suggested that parents' time and efforts in selecting and monitoring private tutoring are associated with increased academic performance (Park et al., 2011). Since home education resources signify the extent of educational resources provided by parents to their children, I tested whether heterogeneity existed in this measure (above or below its mean value).

Fourth, heterogeneity was examined by students' motivation to study. Previous studies have suggested that motivated students, including those who undertaking challenging academic coursework and those with values and behaviors that facilitate academic success, are more likely to benefit from supplemental tutoring (Byun & Park, 2012; Domingue & Briggs, 2009). Therefore, heterogeneity was tested by the hours of students' self-study (above or below mean value).

Finally, for the United States I examined heterogeneity according to students' race/ethnicity. Previous studies have suggested that private supplementary tutoring is particularly effective for East Asian students who tend to be more motivated to study than other racial/ethnic groups (Byun & Park, 2012). Therefore, I tested whether heterogeneity existed by students' race/ethnicity (White, Black, Hispanic, Asian, and others).

Results in Table 4.27 show the heterogeneous effects of participation in two types of tutoring in the United States. Although I obtained estimates using all three methods, I only show the estimates using a kernel method, as all three methods showed similar results and the kernel method was considered the most sophisticated method among the three. For out-of-school tutoring, it has a significant negative effect for those in the third quintile, who have an average likelihood of participating in out-of-school tutoring. When the first to the third quintiles are combined, the result also showed a marginally significant negative effect for this group. There was no significant heterogeneous effect by parental education, hours of self-study, and race/ethnicity. However, out-of-school tutoring had a significantly negative effect on students with fewer home educational resources.

School tutoring had a negative effect for students in the fifth quintile, who are most likely to receive such tutoring. When the fourth and fifth quintiles were combined to represent a group with higher propensities to receive tutoring, school tutoring also showed a negative effect for this group. There was no significant heterogeneous effect by parental education, home educational resources, and hours of self-study. However, school tutoring had a significantly negative effect on Asian students and a significantly positive effect on students of other racial group. For other race/ethnic groups, no significant heterogeneous effects were found.

Table 4.27 Heterogeneous Effects of Tutoring Participation (Kernel), United States

	Out-of-school Tutoring			**School Tutoring**		
	ATT	t		ATT	t	
Quintile=1	23.41	1.28		8.62	.72	
Quintile=2	-21.90	-1.53		2.86	.29	
Quintile=3	-25.74	-2.04	*	10.92	1.29	
Quintile=4	-5.69	-.58		-7.55	-1.08	
Quintile=5	1.04	.14		-10.54	-1.94	*
Quintile<=2	-7.74	-.68		5.25	.69	
Quintile>2	-4.98	-.93		-4.82	-1.13	
Quintile<=3	-15.72	-1.85	+	8.14	1.42	
Quintile>3	-1.13	-.19		-9.45	-2.06	*
College or above	-5.83	-.77		-9.62	-1.58	

High school or below	-5.71	-.97		-.40	-.08
Higher home educational recourses	3.37	.53		-2.95	-.55
Lower home educational resources	-16.18	-2.29	*	-4.35	-.77
More self-study	-3.21	-.48		-3.99	-.67
Less self-study	-2.77	-.40		4.07	.77
Non-hispanic white	-12.08	-1.52		-5.97	-1.18
Black	-1.49	-.14		-4.08	-.43
Hispanic	11.19	1.01		.74	.09
Asian	-8.82	-.43		-47.15	-2.38 *
Other race	.61	.03		37.20	2.04 *

** p<0.01, * p<0.05, + p<0.1

Results in Table 4.28 show the heterogeneous effects of participation in two types of tutoring in Japan. The results show the estimates using a kernel method. For out-of-school tutoring, there was no significant heterogeneous effect by propensity score quintile, parental education, home educational resources, and hours of self study. School tutoring had a significantly negative effect on the students in the first to the third quintiles combined, suggesting that it has a detrimental effect for those who are less likely to receive school tutoring.

Table 4.28 Heterogeneous Effects of School Tutoring Participation (Kernel), Japan

	Out-of-school Tutoring		**School Tutoring**		
	ATT	t	ATT	t	
Quintile=1	-3.66	-.16	-24.68	-1.81	+
Quintile=2	-22.98	-1.35	-4.37	-.49	
Quintile=3	-2.04	-.24	-13.21	-1.40	
Quintile=4	6.50	1.05	8.00	1.15	
Quintile=5	-1.05	-.18	-6.71	-.94	
Quintile<=2	-15.16	-1.11	-10.45	-1.38	
Quintile>2	1.25	.31	-2.94	-.66	
Quintile<=3	-6.68	-.86	-11.84	-1.99	*

Quintile>3	1.86	.43	-.13	-.03
College or above	-.57	-.12	.72	.13
High school or below	.40	.05	-7.18	-1.42
Higher home educational resources	-1.33	-.23	-2.84	-.51
Lower home educational resources	-1.02	-.17	-6.31	-1.17
More self study	-10.26	-1.64	-3.24	-.48
Less self study	9.06	1.63	-2.98	-.66

** p<0.01, * p<0.05, + p<0.1

These results, including differences between the United States and Japan, are further discussed in the next chapter.

Chapter 5
SUMMARY AND DISCUSSIONS

Supplementary tutoring, also known as shadow education, private tutoring, or out-of-school tutoring, refers to a range of organized tutoring practices in academic subjects that occur outside regular school hours. Across societies, many students receive such services, expecting tutoring lessons to have some positive academic impact.

Depending on the nature of supplementary tutoring, its use may have different implications for educational equality. When supplementary tutoring is subject to private demand, meaning that it is privately used by families, more advantaged students may benefit from such tutoring. When supplementary tutoring is provided with public funding, low-income students may benefit more from such tutoring. Therefore, examining the participant characteristics as well as the causal effect of supplementary tutoring on student achievement is necessary for understanding supplementary tutoring, either as a source of educational inequality or as an equalizer of academic achievement.

This study used the 2006 Programme for International Student Assessment (PISA) and compared between the United States and Japan, two countries with similar economic development but different patterns of dominant use of supplementary tutoring. For these two countries, the study addressed the following three questions: (1) What factors affect students' participation in supplementary tutoring in the United States and Japan? (2) What are the effects of supplementary tutoring on students' mathematics achievement in the two countries? (3) Do the effects differ by student subgroups in each country?

This study extended previous research on supplementary tutoring by distinguishing between two types of supplementary tutoring: out-of-school tutoring (taught by non-school teachers) and school tutoring (taught by school teachers), in order to identify the different dimensions of the phenomenon. By separating these two types of tutoring, the study identified specific student characteristics that were associated with each type of tutoring. While out-of-school tutoring was considered to be used mainly on a private basis, school tutoring was considered to be used more publicly among all kinds of students.

In estimating causal effects of supplementary tutoring, selection into participation in tutoring needed to be addressed. Propensity score matching was one possible solution to addressing the selection bias, along with other approaches including instrumental variable method and difference-in-differences method (Morgan & Winship, 2007). Compared to the ordinary least squares (OLS) method, propensity score matching was considered as a more effective approach in reducing selection bias. This method summarized multiple pretreatment characteristics of a subject into a single-dimensional variable, called the propensity score, in order to make the matching feasible (Becker & Ichino, 2002).

Propensity score methods were based on a counterfactual framework, which presupposes two potential outcomes for the same subject; one is an outcome when the subject receives a treatment and the other is an outcome when the subject is under a control. The heart of this method was to create counterfactual groups that are as similar as possible to facilitate comparison between the treated and controlled subjects. In this study, I estimated the Average Treatment effect on the Treated (ATT), which was the difference in achievement outcome for students who *actually received* supplementary tutoring and the potential achievement outcome for the same group of students *had they not received* the treatment. Therefore, unlike OLS estimates that applies to the entire population, ATT focused only on those who are treated.

I compared treated and control cases using propensity scores and removed cases with no comparable matches at the highest and lowest ends of the propensity score distribution. I then matched the treated and control cases using three different techniques to obtain ATT. These matching techniques included pairing subjects (nearest-neighbor method), classifying subjects into strata (stratification method), and weighting subjects according to the propensity score distance (kernel method). Through these semi-parametric matching processes, I claimed that reasonable comparisons were made between the treated and control cases. The three matching methods had a trade-off between quality and quantities of the matching, but their joint consideration offered a way to assess the robustness of the estimates (Becker & Ichino, 2002).

Summary of Main Findings

When participants in supplementary tutoring were compared with non-participants, low-SES and average-achieving students were more likely to participate in *out-of-school tutoring* in

math in the United States. Participants in out-of-school tutoring were more likely to be in public schools, tended to be female, and had the average level of parental occupational status, education level, and wealth. Out-of-school tutored students in the U.S. had more home education resources, had greater interest in learning science, and studied by themselves for more hours than those who were not tutored. Out-of-school-tutored students in the U.S. were more likely to have mothers who are employed, and their schools tended to be larger and located in a large city. As for race/ethnicity, black and Asian students were more likely to participate in *out-of-school tutoring* in the United States.

On the other hand, in Japan, high-SES and high-achieving students were more likely to participate in *out-of-school tutoring*. Participants in out-of-school tutoring were more likely to be in private schools and they tended to have higher parent occupational status, education level, wealth, and home education resources. Out-of-school tutored students in Japan had more interest in learning science and studied by themselves for more hours. Out-of-school-tutored students in Japan tended to be in schools with a higher level of mean parent education and higher level of parental pressure on academic subjects. Their schools tended to be larger and located in cities than in towns, and these schools had better educational resources and were more academically than vocationally oriented.

For *school tutoring* in the United States, low-SES and low-achieving students were more likely to participate in these lessons. Participants in school tutoring were more likely to be in public schools and tended to have lower parental occupation. However, tutored students had better home education resources, had more interest in learning science, and studied longer by themselves. School-tutored students tended to have lower school math achievement. As for race/ethnicity, tutored students were more likely to be Black and Hispanic. They were slightly less likely to speak non-native language at home and tended to be either above or below modal grade. For school characteristics, tutored students were in schools with lower level of mean parental education and higher level of students receiving free/reduced lunch. Their school size tended to be slightly larger and these schools tend to be located in large cities than in small town.

In contrast, slightly high-SES and average-achieving were more likely participated in *school tutoring* in Japan. Participants in school tutoring were more likely to be in private schools and tended to be male. School-tutored students had higher parent occupation, education, home

education resources, and wealth compared to non-tutored students. Tutored students in Japan tended to have greater interest in learning science and studied longer by themselves. Their math achievement was slightly lower than their own school mean achievement. On average, tutored students were in slightly larger schools and experienced greater parental pressure on academic subjects and better school resources. Given these participants' characteristics, out-of-school tutoring in Japan fits the social reproduction model, while school-tutoring in the United States fits the social mobility model.

When I examined the effect of out-of-school tutoring in the United States using propensity score methods, no statistically significant effects were obtained. Similarly, no statistically significant effects for school tutoring in the United States were obtained. However, these suggest that selection bias that existed in the negative direction prior to matching (e.g., low-SES and low-achievement) was removed due to matching. Using the same set of covariates to predict propensity scores, I also estimated the OLS model. While statistically significant negative effect was obtained for out-of-school tutoring in the United States, such significant effect disappeared in the propensity score analysis.

When I examined the effect of out-of-school tutoring in Japan using propensity score methods, no statistically significant effect was obtained. However, this suggests that selection bias that existed in the positive direction prior to matching (i.e., high-SES and high-achievement) was removed due to matching. Similarly, no statistically significant effect for school tutoring in Japan was obtained after matching. Using the same set of covariates, I also estimated the OLS model. The OLS results for both types of tutoring in Japan were largely consistent with the propensity score results.

In addition, I examined how these overall effects may change according to student subgroups. Using the nearest neighbor, stratification, and kernel methods, I examined the heterogeneous effects of tutoring participation on math achievement by the following characteristics: propensity score quintile, parent education level, extent of home education resources, students' motivation to study, and students' race/ethnicity (U.S. only). For out-of-school tutoring in the United States, no heterogeneous effects were found by propensity score quintile, except for the significant negative effect for those in the third quintile. For school tutoring, while it had a positive effect (although nonsignificant) for students on or below the third

quintile (who are less likely to receive school tutoring), it had a negative effect for students on or above the fourth quintile (who are most likely to receive school tutoring). In the United States, there was no significant heterogeneous effect by parental education and hours of self study on either type of tutoring. Out-of-school tutoring had a weakly negative effect on students with fewer home educational resources. As for heterogeneity by race/ethnicity, school tutoring had a negative effect on Asian students and a positive effect on students of other racial group.

In Japan, out-of-school tutoring had a negative effect on students in the second quintile, who had a relatively low likelihood of receiving tutoring. School tutoring had a negative effect on the students in the first and second quintiles combined, suggesting that it had a detrimental effect for those who are less likely to receive school tutoring in Japan. There was no significant heterogeneous effect by parental education and home educational resources. Out-of-school tutoring had a positive effect (although nonsignificant) on students who study less by themselves, suggesting that it may complement the lack of students' self-learning habits.

The overall results of this study showed no significant effect of either type of supplementary tutoring in two countries. Substantively, this suggests that neither type of tutoring contribute to the disparities in academic outcomes among students. That is, while I observed inequality in student characteristics in terms of the *opportunity* to receive supplementary tutoring, I observed no inequality in academic outcomes in terms of the *consequences* of supplementary tutoring[11].

Some of the negative or no effects found in this study may not be easily comprehensible for all researchers. However, as I suggested in the literature review section, there are possible explanations for negative and no effects. This includes lack of sufficient learning time, low quality of tutoring that is discrepant from formal school curriculum, student disengagement and fatigue, and the group heterogeneity that may mask positive effects. Indeed, recent discussions on

[11] Here, it is necessary to note that PISA does not necessarily measure curriculum-based academic achievement, which is more of a target of supplementary tutoring. While TIMSS (Trends in Mathematics and Science Achievement), the other major international academic achievement test, measures curriculum-based achievement, PISA focuses on how well students are prepared for entering the workforce.

the effectiveness of afterschool programs indicate that we do face some negative or null findings, even though we as researchers want to embrace positive findings for policy's sake (Dynarski, 2015). As previously reviewed, Munoz and Ross (2009) raised some uncontrollable factors that may bias the treatment effect, including the characteristics of tutoring setting, contamination from core academic and other support programs, student interest and motivation, and limitations of standardized achievement tests for measuring tutoring impacts. Heinrich, Meyer and Whitten (2010) also raised insufficient hours on tutoring, lack of continuity in students' daytime and after-school learning environments, quality of instruction, and student motivation as possible factors behind the lack of tutoring effect. Indeed, measuring the impact of tutoring is not as easy as it seems.

Despite all the practical and methodological difficulties in realistically measuring the tutoring effect, this study still sheds light on one clear direction. From the heterogeneity analysis, for school tutoring in the United States, those students with lower propensity to receive tutoring seemed to benefit more from tutoring. For out-of-school tutoring in Japan, those students who studied less by themselves seemed to benefit more from tutoring. Although these results were not statistically significant, it showed some promising directions to be pursued in further studies. Even though the *overall effect* of tutoring may be offset by a variety of situations, such heterogeneity in the effects may be a fruitful way that researchers should continue to investigate for the effect of afterschool tutoring.

Relevance for Theory and Policy

Aside from tutoring used on a private basis, tutoring provided with public funding should be evaluated on its participant characteristics and the program effects. Policymakers and practitioners need to be informed of the way supplementary tutoring operates. This study had a particular emphasis on addressing the selection bias in students' participation in tutoring. However, it is necessary to review measures and mechanisms that possibly explain tutoring participation before the study draws any solid policy implications.

Previous studies have suggested that program evaluation for out-of-school academic lessons needs to consider the aspects including measures of program characteristics, intensity and duration of program use, program quality, and students' engagement in the program (Lauer et al.,

2006; Heinrich et al., 2010). For example, in order to draw specific policy recommendations, data should ideally measure when students started the program, how often and how long students were in the program, what quality of lessons students received from what type of teachers, how much students were engaged, where the lesson took place, and in what format.

Summarizing the literature on out-of-school-time lessons, Lauer and her colleagues suggested the following (2006, p. 307):

> In deciding whether to fund OST [out-of-school-time] programs, policymakers should look at other factors, such as program duration, cost, and implementation issues (e.g., staff recruitment, program location).

Heinrich, Meyer, and Whitten (2010, p. 295) who examined the effect of supplementary tutoring program on students' achievement emphasized that research needs to get "inside the black box" to better understand why certain supplementary tutoring programs may or may not be effective. This, in turn, suggests that we need more theoretical explanations about the possible mechanism of the effect of supplementary tutoring. Numerous variables and mediating mechanisms may exist; we need elaborate theories that can be tested with data. For instance, we may ask if tutoring affect achievement through increased motivation, study skills, social capital, or engagement with adults or peers in the program.

Gordon, Bridglall, and Moroe (2005) suggested in a book titled *Supplementary education: The hidden curriculum of high academic achievement* that school alone cannot close the achievement gap and that high academic achievement is supported by "exposure to family and community-based activities and learning experiences that occur outside of school" (p. 41). The authors argued that supplementary education have the potential to equalize the uneven distribution of a variety of capitals, including human capital, cultural capital, and social capital. By providing additional learning opportunities and empowering students in supplementary tutoring, they believed that students will achieve better.

In addition, recent policy debate and initiatives on "extended school day" may be informative for the academic benefit of supplementary tutoring programs. Advocates of the extended school day indicate that increasing the amount of learning time in formal schooling

improves students' academic outcomes, and supplementary tutoring is part of such strategies to support learning in formal schools (Omer, 2012; Patall et al., 2010). As a related concept, some policy initiatives also emphasize "complementary learning," which is an effort to align out-of-school supports with school supports and to maximize the use of resources available for students' learning and development (Little, 2009; Weiss et al., 2009).

With adequate data and theory to explain the mechanism and the effect of out-of-school supplementary lessons, future studies may provide implications for policymakers and practitioners on how to effectively raise students' academic achievement, how to identify a target group of students who needs additional instruction, and whether certain tutoring programs are achieving their goals to reduce achievement gap between students.

Methodological Issues

Three major methodological issues emerged during the analysis. First, data balancing procedures in propensity score matching necessarily involves researchers' arbitrary decisions. This includes the way to identify the common support region. This study followed the maxima and minima approach (Caliendo & Kopeinig, 2008) as one conventional approach. However, when I stratified propensity scores into several strata, there were cases when possible outliers (with no comparable matches) may have remained. In addition, some previous studies recommend trimming, a more conservative way to estimate treatment effects by further removing cases at the highest and lowest ends of the propensity score distribution (Frisco et al, 2007; Zeiser, 2011). Literature suggests removing below the 2nd percentile and above the 98th percentile as one standard for trimming (Zeiser, 2011). I estimated the results using this trimming method. The propensity score distribution before and after trimming obtained by the trimmed data is presented in the Appendix C. Compared to the results without trimming, a greater number of cases were trimmed both in the treated and control cases, including the treated cases in the highest propensity score range. I regarded this as a potential problem, as treated cases with reasonable counterparts (control cases) may have been lost due to trimming. Despite suggestions in the previous literature, trimming involves arbitrary standard, which may not universally apply for all types of data. This is why I did not impose trimming for the present analysis.

As this account shows, propensity score analysis involves steps that require researchers' own discretions and justifications based on their data in hand. Regarding such practical decisions in propensity score analysis, some researchers suggest that "the choice of method depends on the data situation at hand" (Caliendo and Kopeinig, 2008, p. 47). This applies to a series of data balancing procedures in propensity score matching, including the common support, trimming, and different matching techniques to obtain ATT. The beauty of propensity score methods is that they enable to create truly comparable counterfactual groups by closely examining the data; however, there is "no one best method" in achieving this condition.

Second, propensity score methods involve an issue in representing population characteristics. Researchers have repeatedly noted that when a portion of data is discarded with matching, the data is no longer representative of the population (Glynn et al., 2006; Hoshino, 2009). Although the very process of selecting and matching cases is the advantage of this method, the concern on the loss of information has been addressed by many researchers. By referring to the study by Bryson, Dorsett, and Purdon (2002), Caliendo and Kopeinig (2008, p. 47) advised the following about the discarding of data:

> [W]hen the proportion of lost individuals is small, this poses few problems. However, if the number is too large, there may be concerns whether the estimated effect on the remaining individuals can be viewed as representative. It may be instructive to inspect the characteristics of discarded individuals since those can provide important clues when interpreting the estimated treatment effects.

As an alternative approach to solve this problem, recent studies have shown that propensity score can be used as weights to obtain a balanced sample of treated and controlled cases, by retaining all cases in the analysis (Hirano & Imbens, 2002; Hoshino, 2009; Imbens, 2004). Rosenbaum and Rubin (1983) originally proposed matching, subclassification, and covariate adjustment as three practical applications of propensity scores in their seminal work.

Propensity score weighting is another new approach that adds to these variations[12]. Studies suggest that an analysis using inverse propensity score weights has population-based interpretations (Glynn et al. 2006), meaning that results may be generalized for the whole population. However, the method can be sensitive to the estimated weights (Glynn et al., 2006). I plan to explore this approach in my future study.

Third, propensity score methods often face difficulty in meeting its methodological assumptions. Meeting assumptions is critical in making causal inference. Previous studies have suggested several different ways to check the strongly ignorable treatment assignment (i.e., making sure to include all relevant variables, checking the model fit for estimating propensity scores, and checking covariance balance after matching), recognizing that there is no direct way to assess whether this assumption has been sufficiently met (Hoshino, 2009). This in turn suggests that researchers should not be too dismissive of the conventional ordinary least squares (OLS) method for estimating causal effects. If OLS is conducted in an appropriate way (i.e., meeting all the assumptions), the method may be reliable enough in drawing implications for causality, or at least reinforces the results obtained by other more advanced methods for addressing selection bias (i.e., propensity score matching). The results in this study suggested that regarding the effect of tutoring, by and large, the size of the coefficients obtained by OLS methods were not largely different from the ones obtained by propensity score methods. The standard errors for OLS methods tended to be smaller, however, partly reflecting the smaller sample size used in the propensity score methods.

Conducting propensity score matching using cross-sectional data such as PISA may have methodological limitations. For example, possible inclusion of some covariates (i.e., student motivation), which could have been influenced by the student achievement outcome, may lead to violate this assumption[13]. To avoid this potential problem, the use of longitudinal data would be recommended. In addition, lack of prior achievement in estimating the causal effect on academic

[12] Kernel matching I conducted in this study is based on a similar idea as weighting. For detailed discussions, see Callahan et al. (2010) and Hoshino (2009).

[13] However, the student motivation I used in this analysis was in science, not in math as in the outcome measure, so I believe that is a rather a reasonable proxy for pre-treatment characteristics.

achievement is a major weakness of this study. Just as the OLS regression requires, propensity score methods require that all the variables that predict the outcome to be included in the analysis. Although the current study used science achievement as a proxy and tested the models both with and without the proxy, having data with prior achievement would provide more robust estimates of the effect.

Recommendations for Future Research

Based on the findings and limitations of the current study, I present several recommendations for future research. To begin with, I identify three issues to obtain more plausible estimates of the effect of supplementary tutoring. First, treatment variable must be a valid measure of supplementary tutoring. Although this study established the distinction between out-of-school tutoring and school tutoring using PISA, future study should identify the features of supplementary tutoring in a more direct way, so that the study will be more relevant to policy. Second, a sound theory to predict the mechanism of the causal effect of tutoring is necessary. Future studies should gain more insights into the "black box" of the effect of tutoring, such as by adding theoretically-relevant covariates in the analysis and by using qualitative data to make more substantive interpretation of the mechanism. Third, future study should use longitudinal data, or at least cross-sectional data with prior achievement, to identify the causal effect of supplementary tutoring. With such data, researchers may use propensity score methods as well as other methodological techniques to draw a causal inference, such as difference-in-differences approach, to obtain more valid estimates of the effect of tutoring.

As for technical issues, I have three future tasks. First, sensitivity analysis should be used to check whether unobserved variables simultaneously affect assignment to treatment and the outcome variable, causing a "hidden bias" (DiPrete & Gangl, 2004). Stata's "rbounds" (Rosenbaum bounds) command enables to assess this procedure. Second, ways to obtain robust standard errors for ATT should be examined. For example, the use of bootstrapping option should be explored to see how such option may change the estimation standard errors in propensity score matching (Becker & Ichino, 2002). Third, replicate weights and plausible values, two of the analytical tools in PISA for adjusting design weights and obtaining plausible achievement estimates, should be used in the future analysis.

Furthermore, future studies need to address the non-academic benefits of supplementary tutoring. Although improving students' academic achievement is the primary purpose of supplementary tutoring, supplementary tutoring may support non-cognitive development of students especially when students are younger (i.e., elementary school students in lower grades). For example, students may gain useful experience by engaging with adults and peers outside the regular school environment. Supplementary tutoring may also have a childcare function. Parents may be satisfied that their children spend time studying under a supervised environment. Although these functions do not directly relate to improving academic outcomes, these non-cognitive benefits of tutoring should also be considered in the policy discussion.

References

Anderson, J. (2011). Push for A's at Private School Is Keeping Costly Tutors Busy. *New York Times*, June 7.

Aronson, J., Zimmerman, J., Carlos, L., & Center, E. (1998). Improving Student Achievement by Extending School: Is It Just a Matter of Time? *West Ed*, April 1998.

Aurini, J. (2006). Crafting Legitimation Projects: An Institutional Analysis of Private Education Businesses. *Sociological Forum, 21*(1), 83-111.

Aurini, J. & Davies, S. (2004). The Transformation of Private Tutoring: Education in a Franchise Form. *Canadian Journal of Sociology, 29*(3), 419-438.

Baker, D. P., Akiba, M., LeTendre, G. K., & Wiseman, A. W. (2001). Worldwide Shadow Education: Outside-School Learning, Institutional Quality of Schooling, and Cross-National Mathematics Achievement. *Educational Evaluation and Policy Analysis, 23*(1), 1-17.

Becker, S. O. & Ichino, A. (2002). Estimation of Average Treatment Effects Based on Propensity Scores. *The Stata Journal, 2*(4), 358-377.

Bray, M. (1999). *The Shadow Education System : Private Tutoring and Its Implications for Planners* (Vol. 61). Paris: UNESCO, International Institute for Educational Planning.

Bray, M. & Kwok, P. (2003). Demand for Private Supplementary Tutoring: Conceptual Considerations, and Socio-Economic Patterns in Hong Kong. *Economics of Education Review, 22*(6), 611-620.

Bray, M. & Silova, I. (2006). The Private Tutoring Phenomenon: International Patterns and Perspectives. *Education in a Hidden Marketplace: Monitoring of Private Tutoring*. New York: Open Society Institute.

Bray, M. (2003). *Adverse Effects of Private Supplementary Tutoring*. Paris: UNESCO International Institute for Educational Planning.

Briggs, D. C. (2001). The Effect of Admissions Test Preparation: Evidence from NELS: 88. *Chance, 14*(1), 10-21.

Buchmann, C., Condro D. J., & Roscigno, V. J. (2010). Shadow Education, American Style: Test Preparation, the SAT and College Enrollment. *Social forces, 89*(2), 435-461.

Byun, S. & Park, H. (2012). The Academic Success of East Asian American Youth. *Sociology of Education, 85*(1), 40-60.

Caliendo, M. & Kopeinig, S. (2008). Some Practical Guidance for the Implementation of Propensity Score Matching. *Journal of Economic Surveys.* 22 (1), 31-72.

Callahan, R., Wilkinson, L., & Muller, C. (2010). Academic Achievement and Course Taking among Language Minority Youth in US Schools: Effects of ESL Placement. *Educational Evaluation and Policy Analysis, 32*(1), 84-117.

Callahan, R., Wilkinson, L., Muller, C., & Frisco, M. (2009). ESL Placement and Schools: Effects on Immigrant Achievement. *Educational Policy, 23*(2), 355-384.

Choi, J. (2012). Unequal Access to Shadow Education and Its Impacts on Academic Outcomes:

Evidence from Korea. Paper Presented at the RC28 Conference, Hong Kong, May 2012.
Cummings, W. K. & Altbach, P. G. (1997). *The Challenge of Eastern Asian Education: Implications for America*. New York: State University of New York Press.
Dang, H. A. (2007). The Determinants and Impact of Private Tutoring Classes in Vietnam. *Economics of Education Review, 26*(6), 683-698.
Dang, H. & Rogers, F. H. (2008). The Growing Phenomenon of Private Tutoring: Does It Deepen Human Capital, Widen Inequalities, or Waste Resources? *The World Bank Policy Research Working Paper* No. 4530.
Dawson, W. (2010). Private Tutoring and Mass Schooling in East Asia: Reflections of Inequality in Japan, South Korea, and Cambodia. *Asia Pacific Education Review, 11*(1), 14-24.
Dehejia, R. H. & Wahba, S. (2002). Propensity Score-Matching Methods for Nonexperimental Causal Studies. *Review of Economics and Statistics, 84*(1), 151-161.
Dierkes, J. (2008). Japanese Shadow Education: The Consequences of School Choice. In M. Forsey, Scott Davies and Geofferey Walford (Ed.), *The Globalization of School Choice?* (pp. 231-248). Oxford: Symposium Books.
Dobbie, W. & Fryer R. G. (2011). *Getting Beneath the Veil of Effective Schools: Evidence from New York City*: National Bureau of Economic Research.
Domingue, B. & Briggs, D. C. (2009). Using Linear Regression and Propensity Score Matching to Estimate the Effect of Coaching on the SAT. *Multiple Linear Regression Viewpoints, 35*(1), 12-29.
Dronkers, J. & Robert, P. (2008). Differences in Scholastic Achievement of Public, Private Government-Dependent, and Private Independent Schools. *Educational Policy, 22*(4), 541-577.
Dronkers, J. A. & Avram, S. (2010). A Cross-National Analysis of the Relations of School Choice and Effectiveness Differences between Private-Dependent and Public Schools. *Educational Research and Evaluation, 16*(2), 151-175.
Dynarski, M., James-Burdumy, S., Moore, M., Rosenberg, L., Deke, J., & Mansfield, W. (2004). When Schools Stay Open Late: The National Evaluation of the 21st Century Community Learning Centers Program: New Findings. *Report submitted to the US Department of Education, National Center for Education Evaluation and Regional Assistance.* Washington, DC: US Government Printing Office.
Dynarski, M. (2015). The $1.2 Billion Afterschool Program that Doesn't Work. Brookings, The Brown Center Chalkboard, 103, March 19, 2015.
Fredricks, J. A., Blumenfeld, P. C., & Paris, A. H. (2004). School Engagement: Potential of the Concept, State of the Evidence. *Review of Educational Research, 74*(1), 59-109.
Glenn, R. J., Schneeweiss, S. & Stu¨rmer, T. (2006). Indications for Propensity Scores and Review of their Use in Pharmacoepidemiology. *Basic & Clinical Pharmacology & Toxicology*, 98: 253-259.
Guo, S. Y. & Fraser, M. W. (2010). *Propensity Score Analysis: Statistical Methods and*

Applications. SAGE Publications.
Gordon, E. W., Bridglall, B. L., & Meroe, A. S. (2005). *Supplementary Education: The Hidden Curriculum of High Academic Achievement*. New York: Rowman & Littlefield Publication Inc.
Harnisch, D. L. (1994). Supplementary Education in Japan: Juku Schooling and Its Implication. *Journal of Curriculum Studies, 26*(3), 323-334.
Heinrich, C. J., Meyer, R. H., & Whitten, G. (2010). Supplemental Education Services under No Child Left Behind. *Educational Evaluation and Policy Analysis, 32*(2), 273.
Hoshino, T. (2009). *Chousa kansatsu deeta no toukei kagaku: Inga suiron, sentaku baiasu, deeta yuugou* [Statistical science in observational data: Causal inference, selection bias, and data merging]. Iwanami Shoten.
Hynes, K. & Sanders, F. (2010). The Changing Landscape of Afterschool Programs. *Afterschool Matters, 12*, 17-27.
Ireson, J. & Rushforth, K. (2004). Private Tutoring: How Prevalent and Effective Is It? *London Review of Education, 2*(2), 109-122.
Ireson, J. & Rushforth, K. (2005). *Mapping and Evaluating Shadow Education.* London: Institute of Education, University of London.
Jacob, B. A. & Lefgren, L. (2004). Remedial Education and Student Achievement: A Regression-Discontinuity Analysis. *Review of economics and statistics, 86*(1), 226-244.
Jones, C. J. (2015). Characteristics of Supplemental Educational Services Providers that Explain Heterogeneity of Effects on Achievement. *Educational Policy,* 29(6), 903-925.
Judson, T. (2010). The Japanese Model. In Why More Students Rely on Tutors: Has High School Gotten Harder or Are Students Seeking Extra Help to Beat the Competition? *The New York Times,* September 26. http://www.nytimes.com/roomfordebate/2010/09/26/why-more-students-rely-on-tutors
Katsillis, J. & Rubinson, R. (1990). Cultural Capital, Student Achievement, and Educational Reproduction: The Case of Greece. *American Sociological Review,* 55 (2), 270-279.
Komiyama, H. (2000). *Juku: Gakkou surimuka jidai wo maeni* [Juku at the era of reduced role of schooling]. Iwanami Shoten.
Kuan, P. Y. (2011). Effects of Cram Schooling on Mathematics Performance: Evidence from Junior High Students in Taiwan. *Comparative Education Review, 55*(3), 342-368.
Lauer, P. A., Akiba, M., Wilkerson, S. B., Apthorp, H. S., Snow, D., & Martin-Glenn, M. L. (2006). Out-of-School-Time Programs: A Meta-Analysis of Effects for at-Risk Students. . *Review of Educational Research, 76*(2), 275-313.
Lee, C. (2005). Korean Education Fever and Private Tutoring. *KEDI Journal of Educational Policy, 2*(1), 99-107.
Lee, J. (2007). Two Worlds of Private Tutoring: The Prevalence and Causes of after-School Mathematics Tutoring in Korea and the United States. *Teachers College Record, 109*(5), 1207-1234.

Lee, S. & Shouse, R. C. (2011). The Impact of Prestige Orientation on Shadow Education in South Korea. *Sociology of Education, 84*(3), 212-224.

Leow, C., Marcus, S., Zanutto, E., & Boruch, R. (2004). Effects of Advanced Course-Taking on Math and Science Achievement: Addressing Selection Bias Using Propensity Scores. *American Journal of Evaluation, 25,* 461-478.

Little, R. & Rubin, D. (2002). *Statistical Analysis with Missing Data [Second Edition]*. . New Jersey: John Wiley and Sons, Inc.

Monbukagakusho. (2008). *Kodomono gakkougai deno gakushu katsudo ni kansuru jittai chosa houkokusho* [A national survey on child's out-of-school learning activities].

Morgan, S. L. & Winship, C. (2007). *Counterfactuals and Causal Inference: Methods and Principles for Social Science.* New York: Cambridge University Press.

Morgan, S. L. (2001). Counterfactuals, Causal Effect Heterogeneity, and the Catholic School Effect on Learning. *Sociology of Education, 74*(4), 341-374.

Mori, I. (2008). The political background of private tutoring: A comparison of Japan and Korea. Paper presented at the 52nd annual conference of the Comparative and International Education Society, New York, 17-21 March.

Mori, I. & Baker, D. (2010). The Origin of Universal Shadow Education: What the Supplemental Education Phenomenon Tells Us About the Postmodern Institution of Education. *Asia Pacific Education Review, 11*(1), 36-48.

Muñoz, M. A. & Ross, S. M. (2009). Supplemental Educational Services as a Component of No Child Left Behind: A Mixed-Method Analysis of Its Impact on Student Achievement. *National Center for the Study of Privatization in Education. Occasional Paper*.

NCTL, National Center on Time and Learning. (2010). The Relationship between Time and Learning: A Brief Review of the Theoretical Research.

NIRA, National Institute of Research Advancement (Sougou kenkyuu kaihatsu kikou). (1997). *Gakushuu juku kara mita nihon no kyouiku* [Japanese education seen from the cram school's perspective].

OECD, Organisation for Economic Co-operation and Development. (2009). *Pisa Data Analysis Manual: Spss Second Edition.*: OECD Publishing.

Park, H., Byun, S., & Kim, K. (2011). Parental Involvement and Students' Cognitive Outcomes in Korea. *Sociology of Education, 84*(1), 3-22.

Patall, E. A., Cooper, H., & Allen, A. B. (2010). Extending the School Day or School Year. *Review of Educational Research, 80*(3), 401-436.

Rohlen, T. P. (1980). The Juku Phenomenon: An Exploratory Essay. *Journal of Japanese Studies, 6*(2), 207-242.

Ruben, D. B. & Rosenbaum, P. R. (1983). The Central Role of the Propensity Score in Observational Studies for Causal Effects. *Biometrika, 70,* 41-55.

Rubin, D. B. (1974). Estimating Causal Effects of Treatments in Randomized and Nonrandomized Studies. *Journal of Educational Psychology; Journal of Educational*

Psychology, 66(5), 688-701.
Russell, N. U. (2002). The Role of the Private Sector in Determining National Standards: How Juku Undermine Japanese Educational Authority. In G. DeCoker (Ed.), *National Standards and School Reform in Japan and the United States* (pp. 158-176). New York: Teachers College Press.
Rutkowski, L. & Rutkowski, D. (2010). *Private and Public Education: A Cross-National Exploration with Timss 2003.* National Center for the Study of Privatization in Education, Research Paper No. 192. Teachers College, Columbia University.
Silova, I. (2010). Private Tutoring in Eastern Europe and Central Asia: Policy Choices and Implications. *Compare: A Journal of Comparative and International Education, 40*(3), 327-344.
Smyth, E. (2009). Buying Your Way into College? Private Tuition and the Transition to Higher Education in Ireland. *Oxford Review of Education,* 35(1), 1-22.
Statistics Korea. (2011). http://kostat.go.kr/portal/english/index.action
Steinberg, M. P. (2011). Educational Choice and Student Participation: The Case of the Supplemental Educational Services Provision in Chicago Public Schools. *Educational Evaluation and Policy Analysis, 33*(2), 159-182.
Stevenson, D. L. & Baker, D. P. (1992). Shadow Education and Allocation in Formal Schooling: Transition to University in Japan. *American Journal of Sociology, 97*(6), 1639-1657.
Sullivan, P. (2010). As Private Tutoring Booms, Parents Look at the Returns. *New York Times*, August 21.
Tansel, A. & Bircan, F. (2006). Demand for Education in Turkey: A Tobit Analysis of Private Tutoring Expenditures. *Economics of Education Review, 25*(3), 303-313.
Tokyo Metropolitan Government. (2008). Charenji shien tokubetsu kashituke jigyou nit suite [Regarding the “challenge support” special loan policy]. http://www.metro.tokyo.jp/INET/OSHIRASE/2008/06/20i6qf03.htm
U.S. Department of Education. (2007). State and Local Implementation of the No Child Left Behind Act: Volume I—Title I School Choice, Supplementary Educational Services, and Student Achievement: A Report from the National Longitudinal Study of No Child Left Behind (NLS-NCLB).
U.S. Department of Education. (2009). State and Local Implementation of the No Child Left Behind Act: Volume Vii—Title I School Choice and Supplementary Educational Services: Final Report.
Vandenberghe, V. & Robin, S. (2004). Evaluating the Effectiveness of Private Education across Countries: A Comparison of Methods. *Labour Economics, 11*(4), 487-506.
Vergari, S. (2007). Federalism and Market-Based Education Policy: The Supplementary Education Services Mandate. *American Journal of Education, 113*(2), 311-341.
Weiss, H. B., Little, P. M. D., Bouffard, S. M., Deschenes, S. N., & Malone, H. J. (2009). *The Federal Role in out-of-School Learning: After-School, Summer Learning, and Family*

Involvement as Critical Learning Supports. Cambridge: Harvard Family Research Project.
Willms, J. D. (2003). *Student Engagement at School: A Sense of Belonging and Participation: Results from PISA 2000*. OECD.
Winship, C. & Morgan, S. L. (1999). The Estimation of Causal Effects from Observational Data. *Annual Review of Sociology*, 25, 659-706.
Yamamoto, Y. & Brinton, M. C. (2010). Cultural Capital in East Asian Educational Systems. *Sociology of Education, 83*(1), 67-83.
Yuki, M., Hashisako, K. & Sato, A. (1987). *Gakushuu juku: Kodomo, oya, kyoushi wa dou mite iruka* [Juku: How children, parents, and teachers view it]. Gyousei.
Zeiser, K. L. (2011). Examining Racial Differences in the Effect of Popular Sports Participation on Academic Achievement. *Social Science Research*, 40(4), 1142-1169.

Appendix A

Measures on Supplementary Tutoring

The following excerpt shows the items from the student questionnaire in PISA 2006. In Q31, it asked the following question: **How much time do you typically spend per week studying mathematics?** *The time spent attending out-of-school-time lessons (at school, at home or somewhere else).* There were five answer categories in response to this question: *No time, Less than 2 hours, 2-4 hours, 4-6 hours*, and *6 or more hours.*

In Q32, it asked the following: **What type of out-of-school-time lessons do you attend currently (if any)?** *These are lessons **in subjects that you are learning at school**, that you spend extra time learning outside of normal school hours. The lessons might be held at your school, at your home or somewhere else. These are **only** lessons in subjects that you also learn at school.* There were six answer categories to this question:

- (a) <One to one> lessons with a <teacher> who is also a teacher at your school
- (b) <One to one> lessons with a <teacher> who is not a teacher at your school
- (c) Lessons in small groups (less than 8 students) with a <teacher> who is also a teacher at your school
- (d) Lessons in small groups (less than 8 students) with a <teacher> who is not a teacher at your school
- (e) Lessons in larger groups (8 students or more) with a <teacher> who is also a teacher at your school
- (f) Lessons in larger groups (8 students or more) with a <teacher> who is not a teacher at your school.

As it is clear, Q31 identifies out-of-school supplementary tutoring in mathematics, but does not identify the provider. Q32 identifies the provider (school teacher or non-school teacher)

but does not distinguish subjects of tutoring. Therefore, I combine these two items to obtain the measure on school & out-of-school supplementary tutoring in math. If students answered yes to Q31 and chose schoolteachers (a, c, e) as an instructor, I construct a “school tutoring” dummy. If students answered yes to Q31 and chose non-schoolteachers (b, d, f), I construct a “non-school tutoring” dummy.

Appendix B

OLS Results

Table D1 The Effect of *Out-of-school Tutoring* on Mathematics Achievement (OLS), United States

	Model 1			Model 2			Model 3		
	Coef.	Std. Err.		Coef.	Std. Err.		Coef.	Std. Err.	
Out-of-school Tutoring	**-14.038**	**5.193**	******	**-11.699**	**4.015**	******	**-5.641**	**1.996**	******
Private-funded school				4.323	7.715		4.885	5.467	
Female				-18.684	2.104	**	-9.613	1.312	**
Highest parental occupational status				0.617	0.077	**	0.061	0.049	
Highest educational level of parents				5.159	1.151	**	1.161	0.613	+
Home educational resources				1.426	1.191		-0.601	0.605	
Wealth				-1.543	1.331		2.262	0.677	**
General interest in learning science				10.841	1.104	**	-0.618	0.647	
Regular lessons in math				7.384	1.916	**	1.699	0.966	+
Regular lessons in math, squared				-0.121	0.258		-0.025	0.130	
Self study in math				20.586	4.816	**	1.564	2.733	
Self study in math, squared				-3.687	0.865	**	-0.245	0.481	
Mother full-time				1.818	2.606		1.571	1.419	
Mother part-time				8.416	3.124	**	0.725	1.946	
Black				-46.801	4.541	**	-7.198	2.746	*
Hispanic				-19.248	3.693	**	-0.806	2.158	
Asian				12.076	5.550	*	9.514	3.044	**
Other race				-10.427	4.823	*	-3.168	2.755	
Language at home				-0.476	4.515		-10.950	2.861	**
Above modal grade				20.374	3.111	**	6.662	1.801	**
Below modal grade				-47.474	4.092	**	-13.624	2.055	**
School mean parental education				22.105	4.585	**	10.137	3.026	**

School in town				6.310	5.021		-0.544	3.776	
School in city				1.937	6.124		-3.264	4.099	
School in large city				2.316	6.842		-5.003	5.273	
Shortage of math teachers				2.435	1.933		3.219	1.355	*
Parent pressure on academic standards				-7.797	3.767		-1.499	2.232	
School size				-0.002	0.002		0.001	0.002	
Student-teacher ratio				0.482	0.447		0.274	0.281	
Quality of educational resources				1.697	1.855		-0.485	1.327	
% receiving free/reduced lunch				-0.306	0.103	**	-0.015	0.066	
Science achievement							0.689	0.007	**
Constant	489.061	3.698	**	300.263	23.939	**	78.081	16.978	**
N	4274			4274			4274		
R2	0.002			0.395			0.807		

[Model 1 only includes out-of-school tutoring as a covariate. Model 2 includes all covariates except
for science achievement. Model 3 includes all covariates.
Robust standard errors are shown after adjusting for clustering within schools.]
** p<0.01, * p<0.05, + p<0.1

Table D2 The Effect of *School Tutoring* on Mathematics Achievement (OLS), United States

	Model 1			Model 2			Model 3		
	Coef.	Std. Err.		Coef.	Std. Err.		Coef.	Std. Err.	
School Tutoring	**-29.576**	**4.105**	******	**-21.450**	**3.327**	******	**-2.491**	**1.582**	
Private-funded school				1.943	7.857		3.314	5.358	
Female				-18.653	1.960	**	-9.991	1.244	**
Highest parental occupational status				0.582	0.077	**	0.041	0.047	
Highest educational level of parents				4.280	1.150	**	0.957	0.631	
Home educational resources				1.228	1.177		-0.579	0.573	
Wealth				-0.264	1.274		2.844	0.635	*
General interest in learning science				11.586	1.059	**	-0.192	0.647	

Regular lessons in math				7.760	1.868	**	1.840	0.902	*
Regular lessons in math, squared				-0.182	0.254		-0.030	0.124	
Self study in math				22.853	4.681	**	2.866	2.592	
Self study in math, squared				-4.142	0.837	**	-0.503	0.445	
Mother full-time				1.626	2.413		2.017	1.256	
Mother part-time				8.713	2.983	**	0.927	1.844	
Black				-46.036	4.550	**	-5.515	2.585	
Hispanic				-20.558	3.645	**	-0.988	2.211	
Asian				10.352	6.323		9.891	3.162	**
Other race				-6.189	4.985		-2.663	2.795	
Language at home				3.144	4.217		-11.459	2.655	**
Above modal grade				20.289	2.936	**	6.974	1.667	**
Below modal grade				-50.577	3.836	**	-13.315	2.081	**
School mean parental education				20.522	4.680	**	9.599	3.018	**
School in town				6.985	5.107		-0.806	3.711	
School in city				2.170	6.095		-4.111	4.040	
School in large city				6.558	6.809		-4.150	4.945	
Shortage of math teachers				1.368	1.929		3.236	1.315	*
Parent pressure on academic standards				-6.540	3.914	+	-2.105	2.283	
School size				-0.004	0.002		0.001	0.002	
Student-teacher ratio				0.450	0.433		0.218	0.268	
Quality of educational resources				0.923	1.874		-0.772	1.295	
% receiving free/reduced lunch				-0.312	0.101	**	-0.029	0.068	
Science achievement							0.695	0.007	**
Constant	488.509	3.685	**	311.259	23.182	**	80.997	16.882	**
N	4612			4612			4612		
R2	0.014			0.399			0.810		

[Model 1 only includes out-of-school tutoring as a covariate. Model 2 includes all covariates except for science achievement. Model 3 includes all covariates.
Robust standard errors are shown after adjusting for clustering within schools.]
** p<0.01, * p<0.05, + p<0.1

Table D3 The Effect of *Out-of-school Tutoring* on Mathematics Achievement (OLS), Japan

	Model 1		Model 2			Model 3		
	Coef.	Std. Err.	Coef.	Std. Err.		Coef.	Std. Err.	
Out-of-school Tutoring	**50.335**	**6.555 ****	**2.547**	**3.620**		**1.103**	**2.335**	
Private-funded school			-38.323	6.029	**	-13.117	3.139	**
Female			-16.685	3.264	**	-17.113	1.813	**
Highest parental occupational status			0.240	0.075	**	0.169	0.047	**
Highest educational level of parents			1.182	1.014		-0.306	0.652	
Home educational resources			2.330	1.361	+	-0.308	0.786	
Wealth			-0.383	1.265		2.735	0.699	**
General interest in learning science			16.688	1.252	**	0.572	0.807	
Regular lessons in math			7.937	3.452	*	-1.357	1.520	
Regular lessons in math, squared			-0.227	0.358		0.386	0.169	*
Self study in math			17.518	4.925	**	1.192	3.024	
Self study in math, squared			-2.448	0.910	**	-0.403	0.557	
School mean parental education			61.176	6.846	**	18.895	3.599	**
School in town			-9.146	12.120		-4.586	5.637	
School in city			-13.176	12.184		0.735	5.425	
School in large city			-7.674	12.800		3.486	5.846	
Shortage of math teachers			1.518	5.007		3.292	2.230	
Parent pressure on academic standards			12.377	4.666	**	4.988	2.420	*
School size			0.013	0.009		0.001	0.004	
Student-teacher ratio			-0.889	0.698		-0.446	0.353	
Quality of educational resources			2.900	2.494		0.056	1.389	
Vocational orientation			15.628	8.088	+	4.369	4.036	
Science achievement						0.689	0.011	**
Constant	522.273	4.776 **	142.681	36.023	**	44.749	17.957	*
N	4358		4358			4358		
R2	0.029		0.426			0.771		

[Model 1 only includes out-of-school tutoring as a covariate. Model 2 includes all covariates except

for science achievement. Model 3 includes all covariates.
Robust standard errors are shown after adjusting for clustering within schools.]
** p<0.01, * p<0.05, + p<0.1

Table D4 The Effect of *School Tutoring* on Mathematics Achievement (OLS), Japan

	Model 1		Model 2			Model 3		
	Coef.	Std. Err.	Coef.	Std. Err.		Coef.	Std. Err.	
School Tutoring	**0.495**	**5.973**	**-11.967**	**3.752**	******	**-4.029**	**2.208**	**+**
Private-funded school			-36.992	6.096	**	-12.650	3.105	**
Female			-16.378	3.228	**	-16.469	1.760	**
Highest parental occupational status			0.197	0.073	**	0.144	0.047	**
Highest educational level of parents			1.416	0.987		-0.140	0.635	
Home educational resources			2.226	1.315	+	-0.511	0.754	
Wealth			-0.623	1.191		2.742	0.646	**
General interest in learning science			15.932	1.168	**	0.010	0.741	
Regular lessons in math			6.066	3.121	+	-1.592	1.306	
Regular lessons in math, squared			-0.003	0.329		0.428	0.148	**
Self study in math			18.970	4.765	**	1.893	2.969	
Self study in math, squared			-2.447	0.854	**	-0.347	0.534	
School mean parental education			58.667	6.734	**	16.733	3.497	**
School in town			-5.526	11.436		-2.680	5.058	
School in city			-11.889	11.468		1.708	4.822	
School in large city			-8.448	12.142		2.626	5.253	
Shortage of math teachers			3.001	5.442		3.302	2.330	
Parent pressure on academic standards			12.787	4.685	**	4.083	2.352	
School size			0.017	0.008	*	0.005	0.004	
Student-teacher ratio			-0.953	0.697		-0.556	0.351	
Quality of educational resources			2.609	2.506		-0.198	1.358	
Vocational orientation			12.662	7.844		2.843	3.855	

Science achievement							0.693	0.012	**
Constant	522.273	4.776	**	145.373	35.732	**	51.708	17.550	**
N	5108			5108			5108		
R2	0.000			0.412			0.769		

[Model 1 only includes out-of-school tutoring as a covariate. Model 2 includes all covariates except for science achievement. Model 3 includes all covariates.

Robust standard errors are shown after adjusting for clustering within schools.]

** p<0.01, * p<0.05, + p<0.1

Appendix C

Propensity Score Distribution with Trimming

Table E1 Summary of Propensity Scores, *Out-of-school Tutoring*, United States

	Treated (Tutored)					Control (Non-tutored)				
	N	Mean	SD	Min	Max	N	Mean	SD	Min	Max
Propensity scores	347	.125	.074	.009	.411	3965	.077	.058	.003	.511
Off common support						42	.060	.146	.003	.511
Trimmed (below 2%)	1	.009	.	.009	.009	86	.009	.002	.003	.011
Trimmed (above 2%)	22	.305	.035	.265	.411	64	.317	.051	.263	.511

Table E2 Summary of Propensity Scores, *School Tutoring*, United States

	Treated (Tutored)					Control (Non-tutored)				
	N	Mean	SD	Min	Max	N	Mean	SD	Min	Max
Propensity scores	646	.200	.114	.020	.630	3966	.130	.085	.011	.730
Off common support						34	.057	.163	.011	.730
Trimmed (below 2%)	1	.020	.	.020	.020	92	.021	.004	.011	.026
Trimmed (above 2%)	47	.478	.058	.406	.630	46	.476	.068	.401	.730

Table E3 Summary of Propensity Scores, *Out-of-school Tutoring*, Japan

	Treated (Tutored)					Control (Non-tutored)				
	N	Mean	SD	Min	Max	N	Mean	SD	Min	Max
Propensity scores	486	.198	.113	.008	.584	4402	.089	.093	.001	.556
Off common support						536	.005	.002	.001	.008
Trimmed (below 2%)						97	.002	.001	.001	.003
Trimmed (above 2%)	37	.447	.057	.375	.584	61	.416	.039	.373	.556

Table E4 Summary of Propensity Scores, *School Tutoring*, Japan

	Treated (Tutored)					Control (Non-tutored)				
	N	Mean	SD	Min	Max	N	Mean	SD	Min	Max
Propensity scores	706	.178	.079	.030	.466	4402	.132	.073	.017	.510
Off common support						91	.030	.051	.017	.510
Trimmed (below 2%)	2	.030	.000	.030	.030	101	.026	.004	.017	.031
Trimmed (above 2%)	32	.372	.037	.330	.466	70	.364	.035	.326	.510