The Effectiveness of Cram Schools as Inputs of Education Production

Yan Lau*

July 2016

Abstract

Cram schools are supplemental shadow education services offered to students for a fee, and for some, attending them represents a significant portion of total studying time. Using Programme for International Student Assessment (PISA) data, regression analyses indicate that one additional hour per week of attending cram school causes a 0.09 to 0.13 standard deviation increase in test scores. Understanding cram schools as an input in education production is crucial for efficiency and equity reasons; significant resources are devoted to the sector in East and Southeast Asia (this paper's focus region), and differential access can exacerbate economic inequality.

JEL Codes: I20, I25

Keywords: Education, human capital, shadow education, cram schools, PISA

*Assistant Professor, Economics Department, Reed College
Address: 3203 SE Woodstock Blvd, Portland, OR 97202, USA
Email: yanlau@reed.edu | Tel: +1 (503) 517-7676

I Introduction

Education plays a central role in driving economic development and human capital accumulation. From the parents' perspective, investments in their child's education can result in better academic achievement at school and higher incomes later in his or her life. However, families may deem the often-free public education that the student receives to be insufficient. For such families, the gap can be filled by private investments in "shadow education", defined as "a set of educational activities that occur outside formal schooling and are designed to enhance the student's formal school career" (Stevenson and Baker, 1992). There are many types of shadow education services, including internet-based video tutorials, correspondence courses, one-on-one tutoring, and group tutoring sessions conducted outside the home. The latter, while known by many names in various countries[1], are commonly referred to as "cram schools" and will be the focus of this paper. More specifically, cram schools are commercial companies offering supplemental shadow education services to groups of students for a fee, and are multimillion-dollar industries in countries across the world.

The objective of this paper is to examine whether cram school attendance affects academic achievement. In particular, how does one additional hour of cram school attendance affect test scores? To answer this question, I estimate the education production function of students in terms of their allocation of study time, using cross-country survey data that details time spent in different categories of studying, one of these being hours of cram school attendance.

Understanding cram school attendance as an input in education production is crucial both for individual households with students and for the economy as a whole. For many students, services at cram schools make up a significant portion of their total time studying, and for these families, attendance represents a sizable fraction of their education spending. In Vietnam, 31.0% of households spend between 1% and 5% of total expenditure on private tutoring, with another 3.3% spending even more (Dang, 2007). Citing the Korea National

[1]In Japan, they are known as *juku*; in Korea, they are called *hagwon*; in Singapore and Malaysia, they are referred to as tuition centers; in Indonesia, they are named *bimbel*; and in Chinese-speaking places such as China, Hong Kong, and Taiwan, they are called *buxi*.

Statistical Office, Byun (2014) notes that in 2010, the average Korean family spent 240,000 Won (about US$200) on shadow education services every month. According to a 2001 survey of grade 7 students in Taipei, 72.9% of students reported receipt of tutoring, averaging 6.5 hours per week (Liu, 2012). With so much household resources (time and money) invested in cram school attendance, measuring the size of their return on investment is an important task. A related issue is whether time spent in cram schools is the most effective way to produce human capital compared to other avenues for using study time (such as self-studying, parent-supervised studying, or private one-on-one tutoring).

The effectiveness of cram schools is an important topic of study because the sector represents a growing part of many national economies and has been spreading to different countries around the world (Bray, 2009). In Japan, the Yano Research Institute estimates that "during the 2012 fiscal year, the private preparatory school market in Japan was valued at $9.2 billion" (Nagano, 2014). Bray and Lykins (2012) cite a 2010 survey which estimates the Hong Kong cram school market for secondary school students alone was worth HK$1.98 billion (US$255 million). Given that cram schools constitute such large part of the overall economy, it would be a massive misallocation of resources if cram school services did not improve academic achievement.

Many observers have pointed out that cram schools (as well as other shadow education services) can have implications for inequality (Bray, 2009; Byun, 2014; Dang and Rogers, 2008). Their uptake mainly by higher-income households (Byun, 2014; Dang, 2007; Dang and Rogers, 2008; Stevenson and Baker, 1992) can exacerbate education and economic inequality via differential access to presumably higher-quality (shadow) education. This is especially concerning if cram school attendance is a substitute for regular schooling, as high-income households will have less of an impetus to demand better-quality education at regular public schools. On the other hand, if cram schools offer a way for low-income students to access tutoring services in groups—services which they would not otherwise be able to afford one-on-one—then cram schools may be equity enhancing. Gauging the effectiveness of cram schools at producing human capital is one part of addressing these issues related to inequality.

The answer to the research question is highly relevant to policy makers in government and has implications for the education market. If cram schools are a more effective way to develop human capital relative to other forms of education, then it would be efficient to reallocate resources towards the provision of cram school services away from other alternatives. One possibility is to offer subsidies for cram school services (i.e. a price shift), possibly targeted at low-income households. On the other hand, if regular schooling is relatively more effective versus cram school attendance, then one possible policy is to direct resources towards extending the number of hours in a school day (i.e. a quantity shift).

The analysis in this paper focuses on education systems in East and Southeast Asia (see Table 1). While cram schools and other forms of shadow education are prevalent around the world (Baker et al., 2001; Bray, 2009), "the shadow education system of private supplementary tutoring... has historically been most visible in East Asia" where there are "long traditions of private tutoring" (Bray and Lykins, 2012). Bray and Lykins (2012) also argue that as a result of Confucian influences (p. 25), certain parts of Southeast Asia "may be grouped with East Asia" (p. 69). Accordingly, much of the existing body of literature addressing the effectiveness of cram schools concentrates on these two regions as well.

Byun (2014) applies propensity score matching to the Korea Education Longitudinal Study (KELS) and finds that cram schools had a small positive impact on gains in math achievement. Ryu and Kang (2013) go further with the same KELS data and implement multiple econometric approaches. They find that the effect of private tutoring expenditures on test scores remains small. Dang (2007) uses household survey data from Vietnam to estimate a positive and significant effect of private tutoring on student performance, noting that "the impact is much stronger at the lower secondary level compared to the primary level, except for the poor [performers]" (p. 696). Liu (2012) use data from the Taiwan Education Panel Survey (TEPS) and finds a significant positive effect of cram schools on analytical ability and performance in math, but noted diminishing returns to additional hours. Analyzing the same TEPS data with propensity score matching methods, Kuan (2011) concludes the effect of cram schools on math performance to be modest, though he notes that better-performing students from more well-off backgrounds experience less of an effect. Cheo and Quah (2005) examine how private tutoring influences academic achievement in students in Singapore. They find that while tutoring has a positive effect for the subject being tutored, crowding out of time spent on other subjects may lead to an overall decline in student outcomes. Studies on cram schools in other parts of the world include Baker et al. (2001), Briggs (2001), Domingue and Briggs (2009), Gurun and Millimet (2008), and Tansel and Bodur (2005). The evidence for positive effects of cram school attendance has been mixed, with Byun (2014) attributing this "to various factors including the broad divergence in the operational definitions of shadow education variables, the choice of dependent variables, and the type of statistical models employed" (p. 40).

Perhaps the most common criticism of the literature is the issue of endogeneity, and whether estimates can be interpreted as causal effects.[2] Students from more well-off families are known to spend more on cram school (and other shadow education) services.[3] These students are also more likely to perform well in the measured academic outcomes for other reasons such as having more involved parents or better innate ability. Effect estimates which do not take such factors into account will suffer from selection bias. Various authors have attempted to address this issue in different ways. Dang (2007) develops a joint Tobit and ordered Probit econometric technique. Ryu and Kang (2013) instrument private tutoring expenditure with an indicator for being first-born, arguing that families spend more on education for firstborns, but that birth order is random. They also utilize other approaches to account for endogeneity, including first-differencing, propensity score matching, and non-parametric bounding.

I contribute to this strand of the literature by applying an instrumental variables (IV) approach to counter possible omitted variable bias when estimating the effect of cram school

[2]Many have pointed this out, including Dang (2007), Dang and Rogers (2008), and Ryu and Kang (2013).
[3]See Byun (2014), Dang (2007), Dang and Rogers (2008), Kuan (2011), and Stevenson and Baker (1992).

attendance on test scores. Cram school attendance among a student's peers is used as an instrument for own attendance. These regressions also include a host of student- and school-level controls to account for possible selection of a student's peer group.

The second contribution of this paper is to conduct the analysis across multiple countries and territories in East and Southeast Asia. While there have been studies such as Baker et al. (2001) that do use cross-country data, almost all studies estimating the effect of cram schools (or shadow education more broadly) focus on one specific location. My use of student-level data from the 2012 Programme for International Student Assessment (PISA) allows for an effective cross-country comparison to be made. Academic achievement (the dependent variable) is consistently measured across countries because all students are administered similar assessments. And although the quality and conditions of cram schools may vary by location, the definition of the variable of interest itself (hours of cram school attendance) will be much more congruous relative to any comparisons made between different research studies, addressing Byun's (2014) criticism quoted above.

To gain further insight into these issues, I first elaborate on the economics behind cram schools in section II. Section III describes the data and sample used in the analysis, the methodology and results of which are presented in section IV. Section V concludes.

II Economics of Cram Schools

Cram schools are commercial companies offering supplemental shadow education services to groups of students for a fee. The main distinction between cram schools and private one-on-one tutoring is the number of students involved, with the former exploiting economies of scale to a certain extent by involving multiple students per instructor. The quality and conditions of cram school varies greatly, ranging from the mom-and-pop variety operating out of homes, to corporate chains with multiple locations housing modern classrooms and the latest sophisticated learning technologies. While there has been a limited trend for smaller class sizes at cram schools (see Nagano (2014)), the vast majority of cram school classes are much larger. At the other extreme, there are examples of popular instructors who deliver lessons in packed "lecture theaters, with overflow rooms operating with video screens" (Bray and Lykins, 2012, p. 2).

Commentators often note that cram schools serve two roles in providing shadow education services: "enrichment" and "remedial".[4] Students who attend cram schools for enrichment seek to supplement lessons at regular school in order to stay ahead of their peers academically. Often, an enrichment strategy attracts high-performing students, and prevails in settings where competition within the education system is fierce. On the other hand, students who attend cram schools for remedial needs seek to supplement lessons at regular school in order to catch up with peers academically. Often, a remedial strategy attracts low-performing students, and prevails in settings where the quality of public education is lacking. Thus, characteristics of the education system in a particular country may determine how cram schools form and the nature of their services offered. At the national level, Baker et al. (2001) hypothesize that a positive correlation between academic achievement and cram school attendance implies an overall enrichment strategy, while a negative correlation implies an overall remedial strategy. Whatever the reason for attending cram school, such selection is likely to lead to omitted variable bias.

Bray and Lykins (2012) summarize the positive and negative aspects of cram school aptly.

> "On the positive side it can promote personal academic development and contribute to human capital for wider economic advance. It may also offer educational resources with more flexibility and better timing than the mainstream sector. But on the negative side, shadow education may exacerbate social inequalities, cause stress for individuals and families, create inefficiencies in education systems, and contribute to forms of corruption." (p. 2)

From the perspective of economics, the implications of cram schools must be considered in

[4] See Baker et al. (2001) and Byun (2014).

terms of efficiency and equity.

Being one of many factors in the production of education and human capital, the quantity of cram school attendance is efficient only if the marginal benefit from the last hour of attendance equals the marginal costs. Such costs include time and money, and must take into account opportunity costs. As such, the efficacy of cram school attendance on student outcomes must be weighed against the efficacy of other education services on which resources can be spent. However, there is reason to believe that the equilibrium quantity of cram school services chosen may not be optimal. The cram school market suffers from information asymmetry as it is often difficult for consumers to gauge the quality of education provided by cram schools. There may also be the tendency to over-consume as cram school services are a positional good (often as a result of the education system's structure). In the case of under-consumption, the government may decide to subsidize cram school services through a voucher scheme, and shift the market price. In the case of over-consumption, the government may consider regulations limiting quantity on the market; examples of such policies include Seoul's 10pm curfew on cram school activities, or Hong Kong's maximum class size of 45 for cram schools.

There may also be inefficiencies in the production of cram school services related to the labor market for teachers. Given the relatively low wages in the public education sector in many countries, high-quality teachers may be incentivized to switch to the private sector and teach at cram schools instead. This leads to a decrease in the quality of regular schools. Another problematic situation is when teachers at regular schools also provide cram school services. This creates perverse incentives where teachers limit the content taught during regular schooling hours, and "encourage" students to attend after-school classes for a fee, where the remaining (and possibly more critical) curricular materials are taught.[5] Better pay for teachers, and regulations banning teachers from "double-dipping" are some policy solutions governments can consider to alleviate such situations.

[5]This has been observed in countries such as India and Bangladesh (Bray and Lykins, 2012), especially in rural areas where there is a lack of monitoring by administrators.

From an equity perspective, cram schools can have implications for inequality (Bray, 2009; Byun, 2014; Dang and Rogers, 2008), with respect to human capital and (later in life) income. Human capital inequality arises because cram schools are fee-charging private enterprises. This means that higher-income households are in a better position to afford and to take advantage of their education services. These households also tend to have higher human capital investments already. Thus, the availability of cram school services widens the gap in human capital accumulation between students from rich and poor households. This in turn will increase income inequality as students grow up and enter the labor market with disparate levels of human capital. In order to keep inequality levels in check, governments may opt to implement certain redistributive policies. Policy makers can target subsidies for cram school services towards low-income families. Regulating the quantity of cram school services would indirectly slow the growth of inequality too, because limiting access to such services disproportionately affects high-income households. Improving public education services or extending the school day can shift students' allocation of time, as they substitute towards regular schooling away from cram schools.

III Data

This paper uses data from the 2012 round of the Programme for International Student Assessment (PISA) to estimate the effect of cram school attendance on test scores. Administered by the Organisation for Economic Cooperation and Development (OECD), the PISA comprises a battery of tests (in math, reading, and science) and surveys conducted every three years in both OECD and select non-OECD countries. Each round of PISA consists of a cross section of randomly sampled 15-year-old students in different schools within a country, who complete the tests and surveys. School administrators are also asked to complete additional surveys, from which school characteristics are derived. Table 1 lists the countries and territories from PISA used in the analysis.

Table 1: Countries and Territories in Sample of Analysis

Abbreviation	Country / Territory Name
HKG	Hong Kong
IDN	Indonesia
JPN	Japan
KOR	Korea
MAC	Macao
MYS	Malaysia
QCN	Shanghai
SGP	Singapore
TAP	Taipei
THA	Thailand
VNM	Vietnam

The unit of observation is the student within a school in a country. The sample of analysis is restricted to students in grades 9 and 10 (or equivalent) at the time of the survey; these grades are the expected grades for students aged 15. Excluding other grades will thereby exclude students who were held back grades and those who skipped ahead. Furthermore, only students from schools where at least 20 students were surveyed are kept in the sample. This is done to ensure that the calculation of peer averages is not affected by outliers in schools with few students. Lastly, the sample is limited to observations with non-missing values for student characteristics.[6]

Table 2 shows the mean and standard deviation of student test scores by country in the three subjects tested. PISA scores are standardized with a mean of 500 and a standard deviation of 100 across all participating countries (including those not in our sample of analysis). These scores measure a student's human capital in each respective subject at the time the PISA tests were administered, and will be used as dependent variables in the regression analyses below. All analyses using these scores follow the weighting procedures as prescribed by the OECD; standard errors are calculated using plausible values and replicate

[6] The exception to this is that missing values for time spent in regular school are imputed in the calculation process. See footnote 9.

Table 2: Mean and Standard Deviation of Scores

Country / Territory	Math	Reading	Science	N
Hong Kong	580.6	562.8	572.3	1724
	(88.8)	(78.1)	(75.6)	
Indonesia	401.1	422.6	406.6	735
	(78.6)	(75.2)	(70.7)	
Japan	551.9	557.1	564.5	2529
	(86.8)	(89.3)	(87.3)	
Korea	563.4	544.9	545.3	2092
	(96.1)	(84.5)	(79.5)	
Macao	565.2	534.0	541.9	2261
	(80.1)	(72.1)	(70.6)	
Malaysia	442.2	418.8	439.3	1388
	(83.2)	(80.4)	(79.3)	
Shanghai	623.9	579.3	590.1	2844
	(95.1)	(75.1)	(77.1)	
Singapore	590.7	561.3	570.3	2506
	(103.0)	(96.3)	(100.8)	
Taipei	578.8	539.6	537.1	2592
	(106.9)	(83.2)	(76.6)	
Thailand	433.1	452.5	449.6	2536
	(82.2)	(76.6)	(75.6)	
Vietnam	527.2	522.8	542.5	2348
	(80.3)	(67.0)	(72.4)	

Note: Standard deviations in parentheses. PISA scores are standardized with mean 500 and standard deviation 100 across all participating countries. Statistics calculated over sample used in the final regressions including all student and school controls.

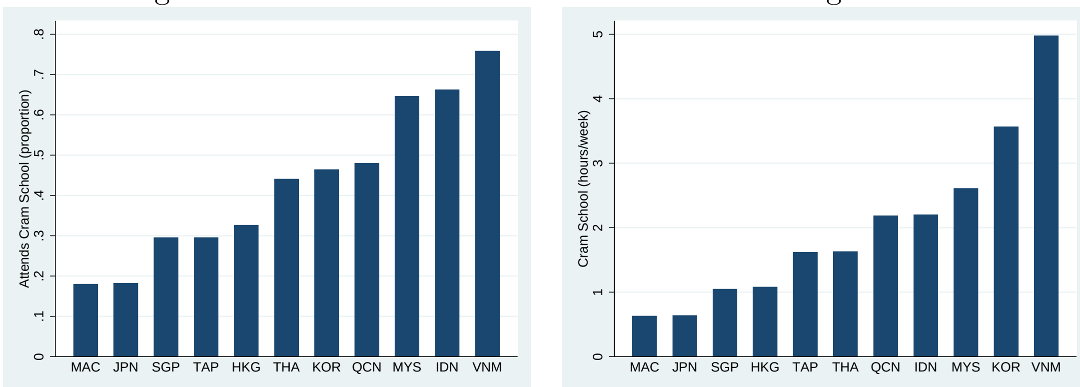
weights.[7] Among the PISA participants used in the analysis, Shanghai obtained the highest mean scores in all three subjects, while Indonesia obtained the lowest mean scores in math and science, with Malaysia obtaining the lowest mean score in reading.

There is sizable variation in cram school attendance across the East and South East Asian region, both in terms of attendance rate and average hours.[8] Figure 1 graphs cram school attendance measured two ways. The left panel shows the proportion of students who report

[7]See OECD (2009).

[8]These data use the following question from the PISA student survey: "Thinking about all school subjects: on average, how many hours do you spend each week on the following? Attend out of school classes organised by a commercial company, and paid for by your parents."

Figure 1: Cram School Attendance Rate and Average Hours



attending (any) cram school by country. This fraction ranges from below 20% in Macao and Japan, to above 75% in Vietnam. The right panel shows the average number of hours students report spending at cram schools by country. Students in Macao and Japan are at the bottom of the range, on average spending around 0.5 hours per week at cram schools. Similar to before, students in Vietnam are at the top of the range, on average spending around 5 hours per week at cram schools.

There is also much variation in cram school attendance within countries. The histograms in Figure 2 show the conditional distribution of cram school hours per week by country. These show only students who reported positive non-zero hours per week. Most countries in the sample have distributions whereby the majority of students attend a few hours of cram school per week. However, Korea, Taipei, and Vietnam have noticeably more spread-out distributions, with a greater number of students attending for longer periods. Still, the vast majority of attending students everywhere do so for less than 10 hours per week.

Table 3 reports additional summary statistics for a selection of other variables from the data. The statistics reiterate the fact that there are large differences in student and school characteristics between countries. Time in school is the number of hours per week of class time at regular school; it is calculated by multiplying the number of periods a student reports attending per week by the length of each period.[9] The proportion of whether either parent

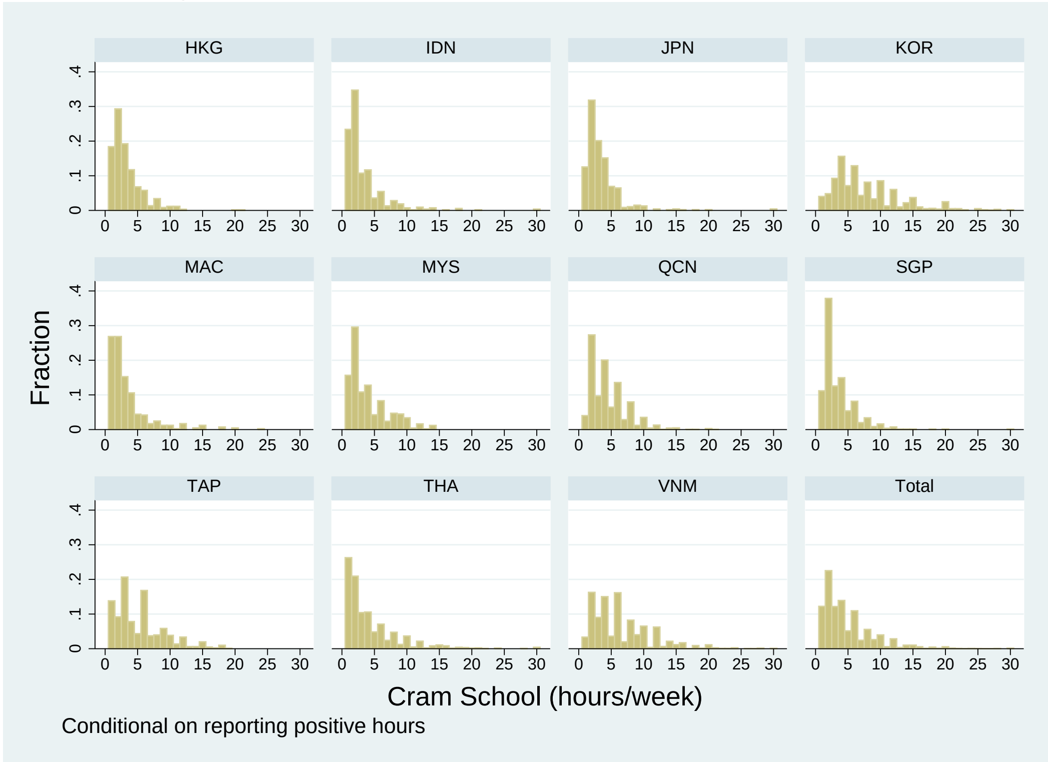
[9]Because of the way this variable is calculated, these hours per week do not include breaks or lunch periods. Cross-validation was done within school to impute missing survey data. All students in a particular

Table 3: Summary Statistics

Country / Territory	Time in School	High School Mother	High School Father	School Characteristics Public	Size	Resources	ST Ratio
Hong Kong	27.2	0.650	0.609	0.993	1046.6	0.442	15.7
	(2.3)	(0.477)	(0.488)	(0.083)	(202.8)	(0.950)	(2.3)
Indonesia	18.8	0.520	0.546	0.765	702.0	-0.541	17.0
	(9.6)	(0.500)	(0.498)	(0.424)	(394.7)	(1.226)	(6.6)
Japan	26.8	0.974	0.948	0.710	766.2	0.422	11.9
	(2.5)	(0.160)	(0.221)	(0.454)	(386.5)	(1.017)	(4.4)
Korea	30.2	0.951	0.946	0.828	1099.1	0.084	16.2
	(3.7)	(0.216)	(0.225)	(0.377)	(409.3)	(0.913)	(3.9)
Macao	27.8	0.409	0.423	0.837	1747.5	0.451	16.2
	(3.9)	(0.492)	(0.494)	(0.370)	(821.6)	(1.038)	(6.1)
Malaysia	28.1	0.829	0.812	0.950	1336.3	-0.082	13.5
	(10.0)	(0.377)	(0.391)	(0.218)	(704.4)	(0.938)	(3.4)
Shanghai	27.4	0.660	0.707	0.896	1469.1	0.143	12.1
	(4.3)	(0.474)	(0.455)	(0.305)	(1047.7)	(1.272)	(5.2)
Singapore	27.1	0.839	0.831	0.971	1369.2	1.216	14.7
	(2.8)	(0.367)	(0.375)	(0.168)	(493.5)	(0.878)	(5.6)
Taipei	32.0	0.834	0.798	0.717	2570.0	0.676	17.4
	(3.1)	(0.372)	(0.401)	(0.450)	(1825.4)	(1.168)	(4.8)
Thailand	31.9	0.386	0.434	0.957	2048.2	-0.627	20.8
	(4.1)	(0.487)	(0.496)	(0.203)	(1220.2)	(1.069)	(5.7)
Vietnam	23.3	0.309	0.373	0.923	1328.6	-0.470	19.1
	(4.6)	(0.462)	(0.484)	(0.267)	(566.3)	(0.976)	(5.3)

Note: Standard deviations in parentheses. Time in school is in hours per week. Public schools include schools which are privately run but government dependent. School resources is an index created by PISA which measures the quality of educational resources available at a school. The student-teacher (ST) ratio is the number of students per full time equivalent teacher at a school. Statistics calculated over sample used in the final regressions including all student and school controls.

Figure 2: Cram School Hours Conditional Distribution



completed high school (or its equivalent) varies greatly between countries, with the highest proportions of over 90% observed in Japan and Korea. The proportion of students in public schools reported in this table is on the higher end, but this may be because the definition of public schools here includes schools which are privately run but government dependent.[10] School resources refers to an index created by PISA measuring the quality of educational resources available at a school. Another measure of school quality is the student-teacher (ST) ratio, which reports the number of students per full time equivalent teacher at a school.

school are assigned the modal reported period length within the school. Should a student's number of periods attending per week be missing or be an outlier from the school median number of periods across all students (defined as an absolute difference of more than 25% from the median), then that observation is replaced with the school's median number of periods.

[10]The subsequent analysis will take these different categorizations into account.

IV Empirical Analysis

To determine the effect of cram school attendance on test scores, I estimate the education production function

$$y_{isc} = \alpha + \beta h_{isc} + T_{isc}\gamma_T + X_{isc}\gamma_X + S_{sc}\gamma_S + \mu_c + \varepsilon_{isc} \quad (1)$$

where

- y_{isc} is test score in math, reading, or science, for student i at school s in country c;
- h_{isc} is the number of hours of cram school attendance reported by student i;
- T_{isc} is a vector of other study time allocations reported by the student in hours per week, which include:
  - time spent doing homework,
  - time spent working with a personal (one-on-one) tutor,
  - time spent studying with parent or other family member,
  - time in regular school[11];
- X_{isc} is a vector of student-level controls, which include an indicator for siblings, grade, sex, age, each parent's education level[12], and each parent's occupational status[13];
- S_{sc} is a vector of school-level controls, which include school type[14], size of student population, the quality of educational resources index, the student-teacher (ST) ratio, and the rate of computer usage[15];

[11]See description in previous section regarding how this value is calculated.
[12]These are categorized using the International Standard Classification of Education (ISCED).
[13]These are measured using the International Socio-Economic Index of Occupational Status (ISEI).
[14]The three categories for this are public, private independent, and private government-dependent.
[15]This is calculated as the number of computers per student at a particular school. Only computers accessible to students designated for educational purposes are counted.

- μ_c is a country fixed effect;

- and ε_{isc} is an error term.

Certain specifications exclude country fixed effects. The coefficient β is the effect of one additional hour of cram school attendance on test score.

However, there is reason to believe that OLS estimates of β will suffer from bias. Omitted variable bias may result from h_{isc} being correlated with unobservables in the error term ε_{isc} not taken into account by the controls. For example, motivation is unobserved to the econometrician; if motivation positively affects both the desire to attend cram school, as well as the potential for obtaining better test scores through hard work, then the estimate of β will be biased upward. There are also concerns about the direction of causality; instead of cram school attendance causing test scores to improve, it could be that high test scores cause students to want to attend cram schools. In order to address such issues of endogeneity, I instrument a student's own cram school attendance h_{isc} with the average cram school attendance of his or her peers in the same school. The first stage of the two stage least squares procedure is

$$h_{isc} = \pi + \lambda \overline{h}_{-isc} + T_{isc}\delta_T + X_{isc}\delta_X + S_{sc}\delta_S + \eta_{isc} \tag{2}$$

where

- $\overline{h}_{-isc}$ is the average number of hours of cram school attendance among all students in school s in country c, except for student i (i.e. the *peer average* cram school attendance);

- η_{isc} is an error term;

and all other notation are as before. In addition to being part of the IV identification strategy, coefficient estimates from this regression will also provide information regarding the characteristics of students who are more likely to take up cram school services.

The validity of the IV identification strategy requires two conditions: the exclusion restriction and non-weak instruments.

Exclusion Restriction For the exclusion restriction to hold, the instrument $\overline{h}_{-isc}$ must be uncorrelated with unobservables in the error term ε_{isc} conditional on the control variables T_{isc}, X_{isc}, and S_{sc}. I argue that having controlled for these student- and school-level characteristics, the peer average cram school attendance is indeed exogenous.

First, consider the situation where the student (or rather, the student's parents) has some say in choosing his or her peers. Suppose high-performing students choose high-performing peers, and all high-performing students make use of cram school services. Then peer average cram school attendance would be correlated with own test score outcomes not through peers influencing own cram school attendance decisions, but rather through a separate avenue. However, students have little say in choosing their peers at that age; it is often the student's parents who have the power to influence a student's peer group through strategies such as choosing which school to enroll the student in. In particular, having highly motivated parents who care greatly about all aspects of their child's life is likely driving this peer group selection. Such motivation on the parents' part will be captured by controls included in X_{isc} and T_{ics}, namely each parent's education level and occupational status, and the amount of time the student spends studying with parents. Furthermore, similar parents would choose similar schools based on certain desired characteristics, which are accounted for by school-level controls in S_{sc}.

However, depending on the policies of the education system, peer group and school selection may be out of the hands of even the most devoted parents. Many education systems in East and Southeast Asia track students into schools using examinations and other forms of assessments, leading to school peers who look very similar to one another. In cases where the peer selection is acting through such government policies, I argue that the school-level controls included in S_{sc} will be sufficient to ensure the exclusion restriction holds.

Governments that track their students into schools almost always do so because they assign different schools with specific allocations of resources to target the type of tracked student. For example, policy may dictate that low-performing students be tracked into schools with low ST ratios to help them learn better. With a host of school quality measures including ST ratios, school size, computer usage rates, and the PISA index of education resources, the variables included in S_{sc} ensure that any remaining variation in $\overline{h}_{-isc}$ after conditioning on these variables is exogenous.

Non-weak Instruments The main argument for why the instrument $\overline{h}_{-isc}$ is correlated with own h_{isc} is that the behavior of the student's peers in attending cram school influences the student's own decision to attend cram school. This peer effect may be due to academic competition. Bray and Lykins (2012) note that "it can become increasingly difficult to keep up with the examination tips and tricks learned by one's classmates [at cram schools]. Students who would not have otherwise sought tutoring may now do so in order not to be at a competitive disadvantage." (p. 31) Another possibility is peer pressure, because all your friends are going to be at cram school. Bray and Lykins (2012) acknowledge this line of reasoning too, asserting that students "seek tutoring chiefly because most of their classmates seem to be doing so." (p. 32) Thus, if the average number of hours per week of cram school attendance among a student's peers increases, that student's own demand for cram school services would increase as well.

IV.A Pooled Results

The first set of estimates is obtained using ordinary least squares (OLS). Student observations from all countries in the sample of analysis are pooled together. Table 4 shows the coefficient estimates for a selection of variables under different specifications of equation (1). Columns (1) through (3) use math test scores as the dependent variable; columns (4) through (6) use reading test scores as the dependent variable; and columns (7) through (9) use science test scores as the dependent variable.

The first specification in columns (1), (4), and (7) of Table 4 regresses equation (1) with only the variable of interest h_{isc}, the full set of time allocations T_{isc}, and country fixed effects. The results from this initial regression reveal that test scores in all three subjects are positively correlated with time spent attending cram school, time spent doing homework, and time spent at regular school. They also show that test scores are negatively correlated with time spent with a private (one-on-one) tutor and time spent studying with a parent or family member. These correlations are all statistically significant. The negative coefficient on private tutor time may arise because students whose family hires a private tutor are likely to be especially struggling, as indicated by lower test scores.

The second specification in columns (2), (5), and (8) of Table 4 adds student-level characteristics X_{isc} as controls to the previous specification. The coefficient on the variable of interest h_{isc} decreases for all three subjects. This is as expected because the inclusion of student controls reduces the positive bias arising from endogeneity. The other coefficient estimates also change slightly, but the overall direction of the correlations remain the same. While many coefficient estimates are suppressed in Table 4 for expositional purposes, I show the estimate for the female indicator to highlight the result that on average, female students receive higher test scores in reading but lower scores in math and science.

The third specification in columns (3), (6), and (9) of Table 4 adds school-level characteristics S_{sc} as controls to the previous specification. Again, the coefficient on the variable of interest h_{isc} decreases for all three subjects, though the extent of this decrease is less than before. Other coefficient estimates remain relatively stable even with the inclusion of school controls. This is the preferred specification. These statistically significant estimates suggest that one more hour per week of attending cram school is associated with a 2.4 point increase in math test scores, and a 1.4 to 1.5 point increase in reading and science test scores. Given that PISA test scores are scaled such that the standard deviation across all participating countries is 100, a 2.4 point increase represents a 0.024 standard deviation increase from one

Table 4: Effect of Cram School Attendance on Test Scores (OLS)

OLS Regression	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dep. Var.:	Math	Math	Math	Reading	Reading	Reading	Science	Science	Science
Cram School	3.208***	2.569***	2.418***	2.131***	1.601***	1.444***	2.132***	1.623***	1.461***
Time	(0.344)	(0.290)	(0.292)	(0.275)	(0.246)	(0.251)	(0.306)	(0.269)	(0.269)
Homework	4.811***	4.235***	4.085***	4.201***	3.509***	3.410***	3.901***	3.414***	3.331***
Time	(0.179)	(0.154)	(0.153)	(0.164)	(0.147)	(0.149)	(0.167)	(0.168)	(0.166)
Private Tutor	-1.732***	-2.362***	-2.384***	-1.614***	-2.012***	-1.991***	-2.034***	-2.526***	-2.461***
Time	(0.499)	(0.429)	(0.427)	(0.442)	(0.416)	(0.416)	(0.423)	(0.375)	(0.368)
Parent Time	-3.058***	-2.613***	-2.506***	-2.305***	-1.958***	-1.927***	-2.724***	-2.362***	-2.297***
	(0.409)	(0.379)	(0.380)	(0.385)	(0.336)	(0.332)	(0.351)	(0.332)	(0.350)
School Time	1.049***	0.821**	0.803**	0.919***	0.748***	0.762***	0.885***	0.708***	0.732***
	(0.354)	(0.322)	(0.334)	(0.292)	(0.266)	(0.275)	(0.281)	(0.246)	(0.259)
Female		-13.694***	-14.165***		23.722***	23.414***		-6.425***	-7.126***
		(1.715)	(1.640)		(1.811)	(1.799)		(1.577)	(1.524)
Educational			3.282*			2.733*			2.521*
Resources			(1.718)			(1.638)			(1.466)
ST Ratio			-0.518			-0.211			-0.309
			(0.406)			(0.359)			(0.344)
Constant	530.1***	436.6***	430.7***	497.8***	408.1***	388.9***	514.4***	400.9***	381.1***
	(10.5)	(50.9)	(50.4)	(8.4)	(48.7)	(48.2)	(8.4)	(47.8)	(47.9)
N	24341	24341	23555	24341	24341	23555	24341	24341	23555
R-square	0.461	0.523	0.523	0.402	0.467	0.469	0.454	0.500	0.500
Country FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Student Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
School Controls	No	No	Yes	No	No	Yes	No	No	Yes

Significance Level: *** = 1%, ** = 5%, * = 10%

Note: All time variables in hours per week. PISA scores standardized with mean 500 and standard deviation 100 across all participating countries. Robust standard errors in parentheses. All regressions include country fixed effects (FEs). Student controls not shown include an indicator for siblings, grade, age, and each parent's education level and occupational status. School controls not shown include school type, size of student population, and the rate of computer usage.

more hour per week of attending cram school.

Although a 0.024 standard deviation effect may seem small compared to other effect sizes in the education policy analysis literature, these numbers should be compared to the coefficient estimates on the (regular) school time variable, which is about 0.7 to 0.8 points (or 0.007 to 0.008 standard deviations). Therefore, in comparison to regular schooling hours, hours spent at cram schools seem to be approximately twice as effective in improving reading and science scores, and almost three times as effective for math scores. Perhaps time spent in school is suffering diminishing returns, given that that amount of time is much greater than the time spent in cram school. As a caveat however, the coefficient estimate on school time may be an under-estimate due to attenuation bias resulting from measurement error in the construction of the school time variable.[16] Lastly, as expected, higher test scores are seen at better quality schools, as measured by the index of education resources (positive coefficient) and ST ratio (negative coefficient, though not statistically significant).

To address endogeneity issues, a second set of estimates is obtained using instrumental variables (IV). A two stage least squares approach is applied where equation (2) is the first stage and equation (1) is the second stage. The same first stage is used for each of the three separate test score outcomes in math, reading and science.

Table 5 shows select coefficient estimates from the first stage of the IV procedure under different specifications of equation (2). As with the pattern before, column (1) consists of only h_{isc}, T_{isc} and μ_c as independent variables, column (2) adds variables in X_{ics}, and column (3) adds variables in S_{cs}. Augmenting the specifications with additional controls does not change the coefficient estimates very much. The preferred specification is the one represented in column (3) with the full set of controls.

These first stage coefficient estimates suggest that peers do influence a student's decision to attend cram school. An increase of 1 hour per week in average cram school attendance by a student's peers is (on average) associated with a 0.67 hour per week increase in that

[16]See the previous section.

Table 5: Effect of Peers on Own Cram School Attendance (IV First Stage)

Dep. Var.: Own Cram School Time	(1) OLS	(2) OLS	(3) OLS
Peer Cram School Time	0.708***	0.678***	0.673***
	(0.024)	(0.024)	(0.028)
Homework Time	0.06***	0.057***	0.058***
	(0.008)	(0.008)	(0.008)
Private Tutor Time	0.212***	0.204***	0.205***
	(0.032)	(0.032)	(0.033)
Parent Time	0.140***	0.142***	0.127***
	(0.024)	(0.024)	(0.023)
School Time	-0.008**	-0.01*	-0.007*
	(0.004)	(0.005)	(0.004)
Has Siblings		-0.04	-0.002
		(0.081)	(0.085)
Female		-0.004	0.017
		(0.063)	(0.063)
Mother's Occupational Status		0.008***	0.009***
		(0.002)	(0.002)
Father's Occupational Status		0.003	0.004*
		(0.002)	(0.002)
Private Government-Dependent School			0.541**
			(0.214)
Public School			0.227***
			(0.079)
Educational Resources			-0.087***
			(0.028)
ST Ratio			0.013
			(0.008)
Constant	-0.227	-3.569*	-3.866*
	(0.178)	(2.033)	(2.075)
N	24341	24341	23555
R-square	0.276	0.281	0.283
F-stat for H0:$\lambda = 0$	883.81	779.92	582.35
Country FEs	Yes	Yes	Yes
Student Controls	No	Yes	Yes
School Controls	No	No	Yes

Significance Level: *** = 1%, ** = 5%, * = 10%

Note: All time variables in hours per week. Robust standard errors in parentheses. All regressions include country fixed effects (FEs). Student controls not shown include grade, age, and each parent's education level. School controls not shown include size of student population and the rate of computer usage.

student's own cram school attendance. This estimate is statistically significant, and the calculated F-statistic confirm that the non-weak instruments condition holds.

The other coefficient estimates in Table 5 offer insight into the characteristics of students who attend cram school. Cram school attendees tend to have motivated parents who on average spend more time studying with their child. The mother having a high-status occupation is significantly associated with more cram school attendance; and the mother's occupation status seems to have a greater impact than the father's occupation status. Students from public or private but government-dependent schools tend to spend more time at cram schools, perhaps using the latter as a substitute for lower quality public education. This quality argument is further validated by the negative and statistically significant coefficient estimate on the educational resources index; the better the resources at a student's regular school, the less hours he or she spends at cram school. The small but negative estimate on the coefficient of school time suggests that cram school services and regular schooling are substitutes, though this estimate is only statistically significant at the 10% level.

Table 6 shows select coefficient estimates from the second stage of the IV procedure under different specifications of equation (1). The columns (1) through (9) and their corresponding specifications mimic exactly those in Table 4. The inclusion of additional controls reduces the coefficient estimate on cram school time slightly; the other coefficient estimates remain fairly stable. The preferred specifications in columns (3), (6), and (9) suggest that a 1 hour per week increase in cram school attendance leads to a 12.9 point increase in math scores, a 9.5 point increase in reading scores, and a 9.3 point increase in science scores. In standard deviation terms, the effect on test score ranges between 0.09 to 0.13 standard deviations for every hour per week of cram school attendance. These IV estimates are about five to six times larger than their corresponding OLS estimates.

The magnitudes and direction of other IV coefficient estimates remain fairly similar to their OLS counterparts from before. Compared to the positive and statistically significant coefficient estimates on time spent doing homework and time spent attending regular school,

Table 6: Effect of Cram School Attendance on Test Scores (IV)

IV Regression	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dep. Var.:	Math	Math	Math	Reading	Reading	Reading	Science	Science	Science
Cram School	16.690***	14.204***	12.886***	12.971***	10.701***	9.480***	12.557***	10.507***	9.345***
Time	(1.694)	(1.721)	(1.708)	(1.389)	(1.430)	(1.444)	(1.403)	(1.464)	(1.486)
Homework	3.68***	3.366***	3.301***	3.292***	2.829***	2.808***	3.026***	2.751***	2.741***
Time	(0.273)	(0.229)	(0.218)	(0.230)	(0.201)	(0.200)	(0.235)	(0.218)	(0.216)
Private Tutor	-4.914***	-4.896***	-4.678***	-4.172***	-3.994***	-3.752***	-4.495***	-4.462***	-4.189***
Time	(0.724)	(0.609)	(0.560)	(0.621)	(0.559)	(0.519)	(0.595)	(0.510)	(0.468)
Parent Time	-4.757***	-4.135***	-3.733***	-3.670***	-3.148***	-2.870***	-4.037***	-3.524***	-3.221***
	(0.624)	(0.534)	(0.506)	(0.550)	(0.460)	(0.437)	(0.484)	(0.418)	(0.419)
School Time	1.176***	0.975***	0.915**	1.021***	0.869***	0.849***	0.983***	0.826***	0.816***
	(0.390)	(0.350)	(0.358)	(0.320)	(0.288)	(0.295)	(0.310)	(0.269)	(0.279)
Female		-14.230***	-14.744***		23.303***	22.969***		-6.834***	-7.563***
		(1.950)	(1.866)		(1.948)	(1.927)		(1.771)	(1.719)
Educational			4.492**			3.663**			3.433**
Resources			(1.830)			(1.660)			(1.569)
ST Ratio			-0.826*			-0.447			-0.541
			(0.468)			(0.398)			(0.394)
Constant	516.8***	469.8***	466.0***	487.2***	434.1***	416.0***	504.1***	426.3***	407.7***
	(11.6)	(56.2)	(53.8)	(9.1)	(52.1)	(50.9)	(9.1)	(51.4)	(50.5)
N	24341	24341	23555	24341	24341	23555	24341	24341	23555
R-square	0.269	0.382	0.408	0.241	0.356	0.382	0.315	0.401	0.421
Country FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Student Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
School Controls	No	No	Yes	No	No	Yes	No	No	Yes

Significance Level: *** = 1%, ** = 5%, * = 10%

Note: All time variables in hours per week. PISA scores standardized with mean 500 and standard deviation 100 across all participating countries. Robust standard errors in parentheses. All regressions include country fixed effects (FEs). Student controls not shown include an indicator for siblings, grade, age, and each parent's education level and occupational status. School controls not shown include school type, size of student population, and the rate of computer usage. Cram school time is instrumented with peer average cram school time within student's school.

an hour of cram school is much more effective than either of these two other uses. There are many reasons why cram schools can provide better quality education, including better teachers, more sophisticated education resources, and the use of technology and special pedagogical techniques to enhance learning. This result suggests that there would be marginal economic gains through reallocating time towards cram school attendance and away from other time uses for education production.

The large increase in the effect of cram school attendance on test scores is somewhat surprising, though Ryu and Kang (2013) obtain similar increases when moving from OLS to IV estimates. The direction of the change suggests that the bias in the OLS estimates are negative. There are three possible explanations for this. Firstly, if the bias is the result of selection bias, then this implies that the omitted unobservable in the error term is negatively correlated with cram school hours. In other words, weaker students are the ones selecting into cram schools, implying a remedial (as opposed to an enrichment) strategy. Secondly, the negative bias may be the result of attenuation bias caused by measurement error in the cram school time variable. The IV estimate, which makes use of exogenous variation in the student's peer group's cram school attendance (conditional on the host of controls included), overcomes the negative bias in both these cases and gives the unbiased effect of cram school attendance on test scores.

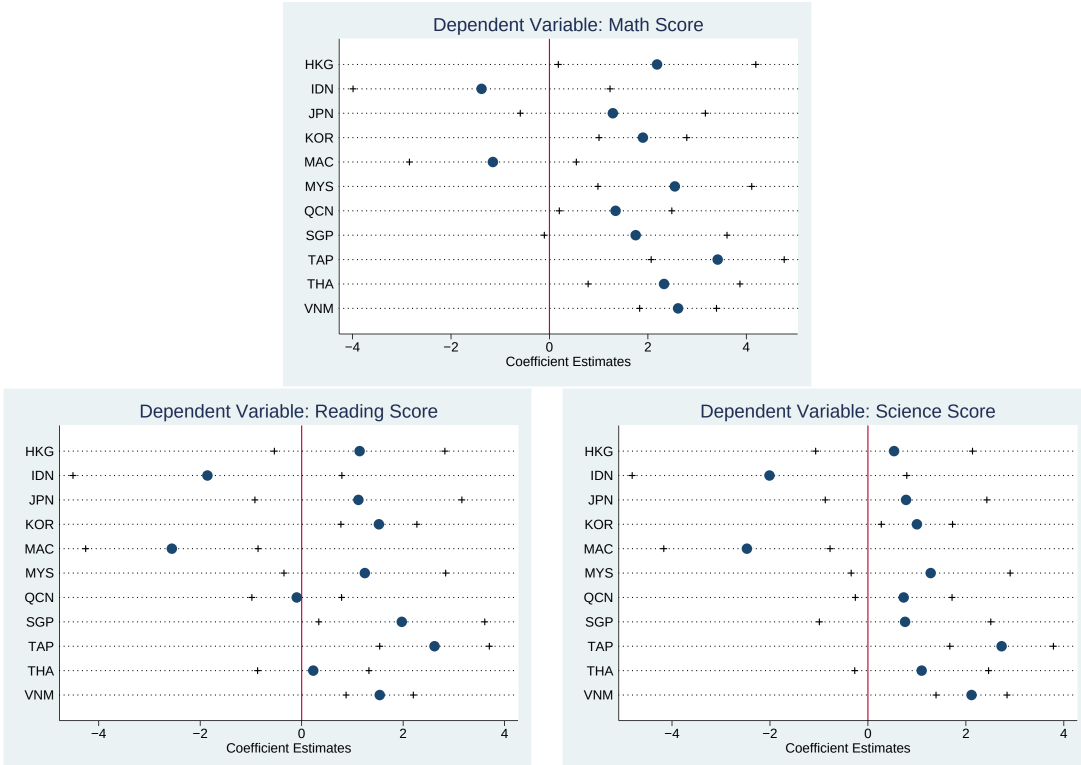
A third possible reason for the increase in the coefficient estimate is that the IV estimator measures the local average treatment effect (LATE) of cram school attendance on test scores. That is, the IV estimate applies only to students who complied with the instrument's influence and were swayed by their peers' attendance of cram school to also attend cram school. Students who are that responsive to peer influences are probably different from the average student. In particular, their capacity to increase cram school hours in response to peers suggests that they are highly motivated to compete with their peers, and that their families have the financial means to spend on cram school services. For such a student, the marginal effect of an additional hour of cram school attendance may be higher than the typical student. Hence, the larger effect size as estimated using IV can be explained through this LATE interpretation. However, I would argue that this LATE estimate still has policy relevance. In a situation where the government subsidizes or provides cram school services, it is precisely this sort of student (motivated, has the means to take up cram schooling) who will respond to such policies incentives.

IV.B Individual Country Results

The results in the previous section suggest that there is a strong positive effect from attending cram schools. However, the estimate uses data pooled across all the countries in the sample of analysis. This may be problematic if the quality and nature of cram school services varies across countries. In particular, social norms, local needs, and the domestic shadow education market may affect what cram school services look like (e.g. mom-and-pop versus large corporate entities). While it will not be possible with the PISA data at hand to get a sense of what precisely cram school services look like, one way to mediate these concerns is to conduct the analysis on a separate, individual country basis, and obtain cram school effect estimates for each country. That is, rerun OLS and IV regressions based on equations (1) and (2) using data from one country at a time. Since each set of regressions comprise a sample from a single country, country fixed effects are excluded. The figures in this section present the results of such a re-analysis, based on the full preferred specification from above, where all student- and school-level controls are included in the regression. The coefficient estimates underlying these figures are presented in full in Appendix Table A.

The three panels in Figure 3 plot the coefficient estimates and their 95% confidence intervals by country, from the OLS regressions for math, reading, and science scores respectively. For example, in the first row of the first panel, the dot at 2.2 indicates that for Hong Kong (HKG), a one hour per week increase in cram school attendance results in a 2.2 point increase in math scores. The lower bound of the 95% confidence interval just crosses the line at 0, indicating that the result is statistically significant at the 5% level. In general, because

Figure 3: Effect of Cram School Attendance on Test Scores by Country (OLS)

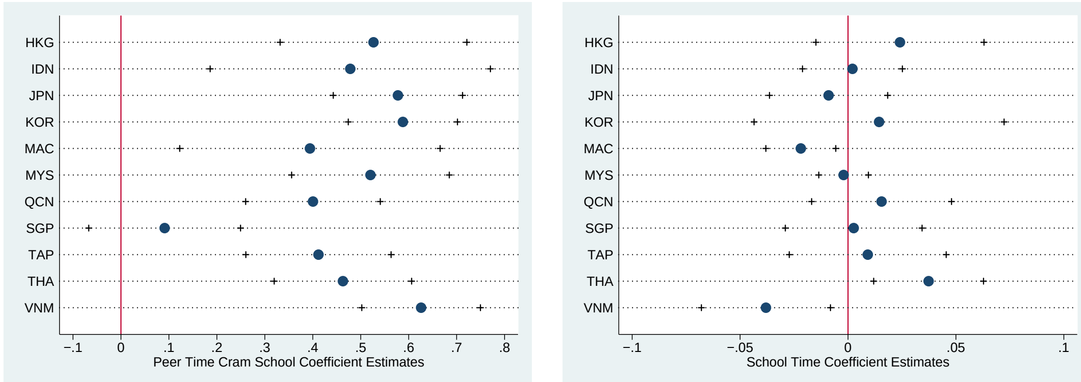


Note: The dots represent coefficient estimates on the cram school time variable. The crosses represent 95% confidence intervals around the coefficient estimates. The OLS regressions used to generate these comprise a full set of student- and school-level controls, but no country fixed effects. PISA scores standardized with mean 500 and standard deviation 100 across all participating countries. See Appendix Table A for underlying coefficient estimates.

each individual regression uses a smaller sample of analysis, the coefficient estimates will be less precise compared to before. However, save for Indonesia and Macao, all of the results are positive and similar in magnitude to the pooled results from previously, ranging between 0 and 3.5, with about half of them being statistically significant at the 5% level. Again however, these OLS estimates may be biased because of endogeneity.

Figure 4 plot the coefficient estimates and their 95% confidence intervals by country, from the first stage of the IV regressions. The left panel shows the coefficient estimates for the peer cram school time variable. Except for Singapore, all coefficient estimates range from around 0.4 to 0.6, and are statistically significant at the 5% level. To check for weak instruments, F-statistics were calculated for each of these countries; only Macao and Singapore

Figure 4: First Stage Effects on Cram School Attendance by Country (IV First Stage)



Note: The dots represent coefficient estimates on the variable indicated on the x-axis title. The crosses represent 95% confidence intervals around the coefficient estimates. The first stage regressions used to generate these comprise a full set of student- and school-level controls, but no country fixed effects. See Appendix Table A for underlying coefficient estimates.

had F-statistics below 10, suggesting weak instruments for these two countries in particular. Otherwise, it seem that across the region, students are heavily influenced to attend cram schools by their peers.

The right panel in Figure 4 shows the coefficient estimates for the (regular) school time variable. All of these estimates are close to zero, and most of them are statistically insignificant, but there are a few notable exceptions. Thailand has a small but positive and statistically significant estimate of 0.04, suggesting that Thai students treat regular and cram schools as complements to one another. On the other hand, Macao and Vietnam have small but negative and statistically significant estimates, suggesting that students here treat regular and cram schools as substitutes for one another.[17]

The three panels in Figure 5 plot the coefficient estimates and their 95% confidence intervals by country, from the second stage of the IV regressions for math, reading, and science scores respectively. Results for Macao and Singapore are excluded because weak first stages resulted in highly imprecise and outlying second stage estimates.[18] As with the pooled data case, using the IV estimator increases almost all the magnitudes of coefficient

[17]It is also interesting to note that these two countries are on the extreme opposite ends of the scale when it comes to cram school attendance rate and average hours of attendance. See Figures 1 and 2.

[18]They were left out for expositional reasons because of how the numbers affect the scale of the x-axes.

estimates significantly. The estimates can be broadly separated into three groups. First, Hong Kong, Japan, Shanghai and Taipei saw the largest increases among all countries. Across all three subjects, the cram school effect size on test scores was around or above 40 points for every hour increase per week. While not definitive, these education systems have relatively low cram school attendance rates and average hours, which suggest that there are still marginal gains in cram school attendance. Second, Korea, Malaysia, Thailand, and Vietnam also saw increases in their coefficient estimates, but the magnitudes of the increases were more moderate. Speculating again, these education systems have relatively high cram school attendance rates and average hours, suggesting that diminishing returns may have set in already with regards to marginal gains from cram school attendance. Lastly, Indonesia is the odd one out, with a negative but statistically insignificant coefficient estimate for all three subjects. This is interesting because Indonesia may actually represent the case where selection bias is in the typical positive direction, and the true causal effect of cram school attendance is actually negligible.

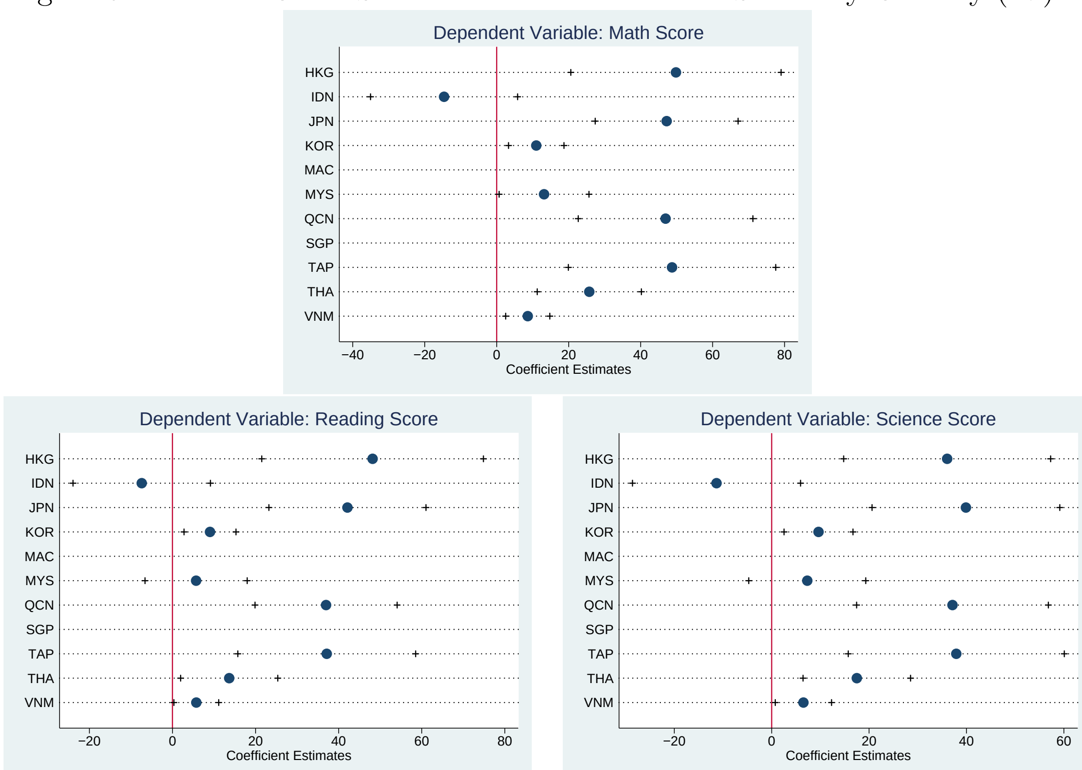
While partitioning the sample by country and re-running the regressions provided interesting insights into variability in the effect size of cram school attendance on test scores, the overall results were more or less similar to and consistent with those of the pooled results.

V Conclusion

This paper estimates the effect of attending cram school on academic achievement. It contributes to existing literature in two ways. First, I develop an IV approach to address possible omitted variable bias by instrumenting a student's own attendance with the attendance of the student's peers. Second, I use the 2012 PISA study which administers the same test and survey to students, thereby allowing for a consistent comparison of results across countries.

The estimates from the pooled analysis suggest that one additional hour per week of attending cram school leads to approximately a 0.09 to 0.13 standard deviation increase in

Figure 5: Effect of Cram School Attendance on Test Scores by Country (IV)



Note: The dots represent coefficient estimates on the cram school time variable. The crosses represent 95% confidence intervals around the coefficient estimates. The IV regressions used to generate these instrument own cram school time with peer average cram school time, and comprise a full set of student- and school-level controls, but no country fixed effects. PISA scores standardized with mean 500 and standard deviation 100 across all participating countries. See Appendix Table A for underlying coefficient estimates.

test scores, depending on whether the subject is math, reading or science. I also estimate the cram school effect for individual countries in order to make international comparisons; these country-specific results are mostly consistent with the overall pooled results.

These findings have policy implications, as they suggest that cram schools provide higher marginal gains in human capital relative to other forms of time use for education production, in particular vis-a-vis time spent by the student doing homework and time spent in regular school. Policy makers can achieve efficiency gains by reallocating time away from other uses towards cram school attendance through measures such as subsidies and a relaxation of regulations (if present) limiting the quantity of cram school services on the market. Equity concerns can also be addressed if policies such as subsidies are targeted towards benefiting low-income households who may otherwise not spend money on cram schools.

While the use of the PISA dataset has the advantages of consistent comparisons, not all cram school services are equal across (or even within) countries. The simplicity of having a single definition for and a clear measure of cram school attendance glosses over more nuanced facets of cram school quality. This is something that one cannot really avoid when using survey data with a broad focus on education. This paper's focus on East and Southeast Asia also limits the scope of comparison. And while most of the literature has also focused on this part of the world, expanding the analysis globally may be a natural next step, as the phenomenon of cram schools is one that is spreading.

References

Baker, David P., Motoko Akiba, Gerald K. LeTendre, and Alexander W. Wiseman (2001) "Worldwide Shadow Education: Outside-School Learning, Institutional Quality of Schooling, and Cross-National Mathematics Achievement," *Educational Evaluation and Policy Analysis*, Vol. 23, No. 1, pp. 1–17.

Bray, Thomas Mark (2009) *Confronting the shadow education system: what government policies for what private tutoring?*, Paris: United Nations Educational, Scientific and Cultural Organization ; International Institute for Educational Planning.

Bray, Mark and Chad Lykins (2012) "Shadow Education: Private Supplementary Tutoring and Its Implications for Policy Makers in Asia," *CERC Monograph Series in Comparative and International Education and Developmentonal*, Vol. 9.

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

Byun, Soo-yong (2014) "Shadow Education and Academic Success in Republic of Korea," in Hyunjoon Park and Kyung-keun Kim eds. *Korean Education in Changing Economic and Demographic Contexts*, Vol. 23 of Education in the Asia-Pacific Region: Issues, Concerns and Prospects: Springer Singapore, pp. 39–58.

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

Dang, Hai-Anh (2007) "The determinants and impact of private tutoring classes in Vietnam," *Economics of Education Review*, Vol. 26, No. 6, pp. 683–698.

Dang, Hai-Anh and F. Halsey Rogers (2008) "The Growing Phenomenon of Private Tutoring:

Does It Deepen Human Capital, Widen Inequalities, or Waste Resources?" *The World Bank Research Observer*, Vol. 23, No. 2, pp. 161–200, April.

Domingue, Ben and Derek C Briggs (2009) "Using linear regression and propensity score matching to estimate the effect of coaching on the SAT," *Multiple Linear Regression Viewpoints*, Vol. 35, No. 1, pp. 12–29.

Gurun, Ayfer and Daniel L. Millimet (2008) "Does Private Tutoring Payoff?" IZA Discussion Paper 3637, IZA.

Kuan, Ping-Yin (2011) "Effects of Cram Schooling on Mathematics Performance: Evidence from Junior High Students in Taiwan," *Comparative Education Review*, Vol. 55, No. 3, pp. 342–368.

Liu, Jeng (2012) "Does cram schooling matter? Who goes to cram schools? Evidence from Taiwan," *International Journal of Educational Development*, Vol. 32, No. 1, pp. 46–52.

Nagano, Yuriko (2014) "A New Ratio for the Japanese Cram School," *The New York Times*, August 10.

OECD (2009) *PISA Data Analysis Manual: SPSS, Second Edition*: OECD Publishing.

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

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

Tansel, Aysit and Fatma Bircan Bodur (2005) "Effect of private tutoring on university entrance examination performance in Turkey," IZA Discussion Paper 1609, IZA.

Table A: Individual Country Estimates from Figures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS			IV First Stage		IV Second Stage		
Dep. Var.:	Math	Reading	Science	Hours of Cram Sch.		Math	Reading	Science
HKG	2.186**	1.142	0.534	0.527***	0.024	49.819***	48.171***	36.034***
	(1.024)	(0.857)	(0.817)	(0.099)	(0.020)	(14.907)	(13.610)	(10.842)
IDN	-1.380	-1.857	-2.010	0.478***	0.002	-14.622	-7.397	-11.327
	(1.332)	(1.352)	(1.430)	(0.149)	(0.012)	(10.426)	(8.437)	(8.804)
JPN	1.288	1.118	0.779	0.578***	-0.009	47.232***	42.115***	39.889***
	(0.960)	(1.041)	(0.842)	(0.069)	(0.014)	(10.129)	(9.645)	(9.834)
KOR	1.899***	1.522***	1.001***	0.588***	0.014	10.995***	9.036***	9.621***
	(0.455)	(0.382)	(0.371)	(0.058)	(0.030)	(3.931)	(3.190)	(3.611)
MAC	-1.149	-2.559***	-2.471***	0.394***	-0.022***	7.932	-104.102***	-60.222**
	(0.865)	(0.867)	(0.866)	(0.139)	(0.008)	(13.550)	(39.516)	(25.544)
MYS	2.548***	1.245	1.282	0.520***	-0.002	13.161**	5.691	7.307
	(0.797)	(0.813)	(0.828)	(0.084)	(0.006)	(6.372)	(6.273)	(6.128)
QCN	1.344**	-0.097	0.730	0.400***	0.016	46.933***	36.972***	37.128***
	(0.583)	(0.451)	(0.504)	(0.072)	(0.017)	(12.383)	(8.726)	(10.046)
SGP	1.752*	1.973**	0.759	0.091	0.003	163.011	87.199	179.547
	(0.947)	(0.835)	(0.893)	(0.081)	(0.016)	(3511.324)	(1914.318)	(3823.965)
TAP	3.418***	2.619***	2.73***	0.412***	0.009	48.729***	37.134***	37.908***
	(0.690)	(0.551)	(0.540)	(0.077)	(0.019)	(14.703)	(10.920)	(11.318)
THA	2.328***	0.228	1.097	0.463***	0.037***	25.733***	13.657**	17.481***
	(0.787)	(0.560)	(0.697)	(0.073)	(0.013)	(7.383)	(5.965)	(5.631)
VNM	2.613***	1.539***	2.116***	0.626***	-0.038**	8.63***	5.739**	6.517**
	(0.398)	(0.338)	(0.370)	(0.063)	(0.015)	(3.128)	(2.752)	(2.948)
Coef. on:	Hours of Cram Sch.			Peer Cram Sch.	Reg. Sch. Hrs.	Hours of Cram Sch.		

Significance Level: *** = 1%, ** = 5%, * = 10%

Note: Each cell is a coefficient estimate from a separate regression specification, using data from the country indicated for that row. All time variables in hours per week. PISA scores standardized with mean 500 and standard deviation 100 across all participating countries. Robust standard errors in parentheses. Student controls not shown include grade, age, and each parent's education level. School controls not shown include size of student population and the rate of computer usage.