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The Causal Effect of the Cram Schooling Timing Decision on Math Scores

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Abstract

We take advantage of Taiwan Education Panel Survey data to evaluate the timing of the coaching effect on mathematics learning for junior high-school students. Our main finding suggests that the best strategy for the budget-limited parents is to send their children to cram schools for intensive learning in the 8th rather than earlier in the 7th grade, in order to enhance the scores for the math tests being held in the 9th grade.

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1 Introduction and Background

The aim of cram schooling is to impart as much information to the students as possible within a short period of time. Students who attend the cram schools are expected to enhance their academic performance in schools, or to pass the entrance examinations for high schools or universities.[1] Due to the keen competition to enter higher levels of schooling, cram schools are much more prevalent in East Asia than in western countries.[2] In the case of Taiwan, Figure 1 shows that the number of general cram schools has increased considerably from 4,984 in 2000 to 18,147 in 2009, indicating a strong and rising demand for cram schooling.[3] According to the Taiwan Youth Project conducted by the Institute of Sociology, Academia Sinica in Taiwan from 2000 to 2006, around 50% of junior high-school students in Taiwan have attended cram schools, and in some areas of metropolitan Taipei this ratio is even up to 80%. This remarkable prevalence of cramming activities in Taiwan arises for three reasons. First, Taiwan has a predominantly ethnic Chinese society with deep roots in Confucianism. The value of meritocracy and the use of competitive examinations to choose among candidates are much emphasized (Zeng, 1999). Second, the institutional characteristics of the educational system in Taiwan contribute to the development of shadow education (Stevenson and Baker, 1992). For instance, formal examinations are adopted, particularly centrally-administered examinations. Finally, there are tight linkages between the outcomes of current schooling and future general status such as educational attainment, occupations and wage offers (Hofferth et al., 1998). From the family economics perspective (e.g., Becker and Tomes, 1986), attending cram schools can be interpreted as the parents' educational investment in their children. Therefore, parents are likely to send their children to cram schools for (possibly) better education and for better future achievement.

Previous studies have demonstrated that the effect of cram schooling on the performance of students is positive (e.g., Becker, 1990; Egan and Bunting, 1991; Stevenson and Baker, 1992; Powers and Rock, 1999), while some research argues that the advantage of coached students is not significant (e.g., Briggs, 2001; Allalouf and Ben-Shakhar, 1998; Scholes and Lain, 1997; Kenny and Stone, 2000; Kenny and Faunce, 2004). The upside of coaching is that it provides more information on how to obtain higher scores on the tests in schools or to be accepted at a prestigious school, e.g., examination-oriented materials and solution techniques are systematically taught in cram schools. However, the downside is that cramming activities may worsen the students' ability to think independently, since attending cram schools may take away too much time for self-learning and digesting materials. Furthermore, teachers in cram schools tend to summarize the academic materials for students and later on students will lack the opportunity to organize the information themselves. Thus, the overall effect of

[1] In Taiwan, the entrance examination for high schools is usually taken by junior high-school students in their 9th grade.

[2] International comparisons in regard to cramming activities can be found in, for instance, Stevenson and Stigler (1992) and Baker et al. (2001).

[3] The trend remains the same for the other three types of cram schools in Figure 1. The data sources are adapted from the 2009 Information Management System of Cram Schools, maintained by the Education Bureau of the Kaohsiung City Government in Taiwan. Please refer to the official webpage: `http://bsb.edu.tw/afterschool/html/statistics.html`.

cram schooling on the students' academic achievement is not clear-cut. As for the positive effects of cram schooling, there is unfortunately rather less discussion in previous studies on the impact on academic performance of the timing in terms of attending cram schools. The decision regarding the timing of engaging in shadow education is crucial, especially for parents with limited budgets. If parents can afford the funding for only a specific time period (say, the 7th or 8th grade), it is informative to know whether it is more efficient to allocate resources to that period in terms of improving the academic outcome (say, an entrance examination held in the 9th grade).

We take advantage of the data set, the Taiwan Education Panel Survey, which keeps track of the students every two years, to evaluate the coaching effect during the period from 2001 to 2005. The first goal of this note is to empirically test whether the causal effect of cram schooling for math learning is significant using data for junior high-school students in Taiwan. Our second goal is to compare the effect of the timing for engaging in cramming activities on academic performance, since students (or their parents) can decide whether they will attend cram schools in their 7th grade, 8th grade or both, or even not to attend. The comparison helps us understand whether it would be beneficial to attend cram schools at the earlier (7th grade) or later (8th grade) stage in junior high schools. This information could also provide students and parents with some useful hints on how to efficiently allocate their time and money.

Typically, uncovering the causal effect of cramming on academic performance may suffer from the endogeneity problem. That is, the test scores and attending cram schools might be correlated with each other or, in other words, the causal relationship may be bi-directional. Evaluating the effect of cramming may also be misleading due to the non-random assignment of attending cram schools. Furthermore, the (observable and unobservable) time-invariant and time-varying confounding factors might result in potential selectivity problems. This paper adopts the fixed effect model that uses the propensity score matching method to deal with the potential selection issues. Nevertheless, if some of the (observable) confounders change with time, the fixed effect estimates will be biased. Therefore, we also check the stability of the time-variant confounders to support the reliability of our empirical findings.[4]

The remainder of this paper is organized as follows. The next section describes the data and econometric methodology utilized for the empirical evaluation. Section 3 presents and discusses our empirical results. The final section concludes.

2 Data and Econometric Methods

The data sets used in our empirical study, the Taiwan Education Panel Survey (TEPS), are collected with the support of Academia Sinica, the Ministry of Education, the National Academy of Educational Research, and the National Science Council in Taiwan, starting with

[4]We are grateful to an anonymous referee for the discussion on the different types of selectivity issues. We acknowledge that it is a limitation of our current approach if there exists an unobserved time-variant confounding factor (e.g., parental death or illness in our context), which cannot be removed through a typical fixed effect model. However, such types of the omitted variable bias problem is always an issue in empirical research.

the year 2001. The main purpose in conducting the TEPS is to longitudinally gather data on a variety of education-related questions from students (e.g., individual characteristics, learning conditions), parents (e.g., family background, interaction with their kids), teachers (e.g., class atmosphere, curriculum plans), and schools (personnel, funding), which can serve as valuable reference to policy-makers within the government as well as researchers.[5] Since the cramming activities are well recorded in more detail for mathematics in the TEPS, we focus on math learning rather than on other subjects. In order to obtain key variables, we match the junior high-school student data in three waves (namely, 2001, 2003, and 2005), and the parents' data in 2001 to generate our sample.[6] The 2001 student data (the first-wave) give the math performance in the 7th grade and the 2003 student data (the second wave) provide the math performance at the beginning of the 9th grade. For the 2005 student data (the third-wave), the students were actually in the 11th grade. However, the questions regarding whether a student attended cram schools in the 7th, 8th, 7th or 8th, and both grades were asked only in this (2005) wave, i.e., the timing of engaging in cram activities could only be obtained in the 2005 wave. There are 3,022 students who were tracked out of 14,083 students in the 2005 data.[7] Therefore, after combining the follow-up student data and the parents' data, and removing unreasonable observations, the sample size is reduced to 1,836.[8]

The dependent variable is the students' performance in mathematics learning, which is measured by the difference in the test scores between the 7th and 9th grades.[9] The original math test score in the TEPS is the Item Response Theory (IRT) score, which is further transformed into a normal curve equivalent (NCE) score for interpretation purposes.[10] Since we care about the effect of timing in attending cram schools on the academic performance, there are four cramming statuses considered in our empirical investigation: 1) attending cram schools either in the 7th or 8th grade or both; 2) attending cram schools in both the 7th and 8th grades; 3) attending cram schools in the 7th grade only; and 4) attending cram schools in the 8th grade only. For the first two statuses, we are able to test the coaching effect. As for the last two scenarios, we can investigate the effect of timing on math performance. We

[5]The students' subject ability tests (including English and Mathematics) and questionnaires are taken and given in the classroom. Questionnaires for parents, teachers (answered by homeroom, Chinese language, English and Math teachers) and schools (answered by the principal and the director of studies) are also gathered by field interviewers.

[6]In fact, the TEPS covers the students in junior high school, senior high school, and five-year junior college. We focus on the junior high-school students in this note due to the completeness of the data.

[7]The reason for losing observations is that it is hard to keep track of the same junior high-school students when they become senior high-school students.

[8]This sample size is obtained when we choose the first-wave (2001) characteristics for propensity score matching, while the sample size declines slightly to 1,367 using the third-wave (2005) data for estimation.

[9]As mentioned, the math tests were taken in the first semester of the 7th and 9th grades, respectively. Kenny and Faunce (2004) indicate that initial test scores may influence the coaching effect so that we take the differenced scores to control a student's initial math ability at the beginning of junior high school.

[10]The NCE score is a normalized standardized score with a mean of 50 and a standard deviation of 21.06 resulting in a near equal interval scale from 0 to 99. The NCE score was developed by RMC Research Corporation in 1976 to measure the effectiveness of the Title I Program across the United States and is often used to measure gains over time. See Tallmadge (1976) for more details.

expect that the timing of the cramming decision matters because it is reasonable to think of the short-run effect of cramming (i.e., the timing being much closer to the date of the tests) as being larger than the long-run effect (i.e., the timing being far from the date of the tests).

Using multiple regression analysis to uncover the causal effect of cramming on academic performance may, however, give rise to the endogeneity problem.[11] This is because test scores and attending cram schools might be correlated with each other; in other words, the causal relationship is bi-directional. Furthermore, the ordinary least squares (OLS) estimator used to evaluate the effect of cramming may be biased due to the non-random assignment of attending cram schools. One can not, for instance, identify the difference between the outcome with the treatment (i.e., attending cram schools) and the outcome without the treatment (i.e., not attending cram schools), because the counterfactual can never be observed.[12] Identifying the causal effect of the treatment employing typical observational data needs another approach. The basic idea behind identifying the treatment effect is to compare the average difference between the treatment and control (i.e., untreated) groups. If the treatment and control groups differ in observed covariates X, then the difference in outcome Y cannot be attributed to the difference in the treatment. The intuitive solution is to compare only those subjects with the same (or similar) values of X across the two groups. Matching subjects on a higher dimensional vector of characteristics is typically unfeasible in practice. We therefore adopt the propensity score matching method (Rosenbaum and Rubin, 1983) to summarize the pre-treatment characteristics of each subject into a single-index variable (i.e., the propensity score $p(X)$) which makes the matching feasible. In general, matching using the propensity score is not sufficient to estimate the treatment effect. The reason is that the probability of observing two units with exactly the same value of the propensity score is in principle zero since the propensity score is a continuous variable. There are several matching methods proposed in the literature to overcome this problem, such as nearest neighbor and kernel matching. See Becker and Ichino (2002) for more details. The description of the pre-treatment characteristics adopted for the propensity score matching method is reported in Table 1.

We have mentioned in the Introduction and Background Section that the selectivity issues due to (observable and unobservable) time-invariant and time-varying confounding factors might also cause the propensity score matching method to be biased, that is, if some (observable) confounder changes with time, the fixed effect estimates will be biased. Note that the pre-treatment variables we have used for the matching method are from the first-wave of data (i.e., characteristics obtained in 2001). To check the stability of the time-variant confounders to support the reliability of our empirical finding, in Section 3.4 we first inspect the change in the observable confounders for the first-and third-waves TEPS data, and conduct a robustness check by replacing the pre-treatment variables with those based on the third-wave data (i.e., the characteristics obtained in 2005).

[11]In an earlier draft, we adopted the instrumental variable approach to overcome the endogeneity problem. Unfortunately, we faced the weak instrument problem which may result in an unreliable inference.

[12]This is known as the "Fundamental Problem of Causal Inference" in Holland (1986).

3 Empirical Results

3.1 Summary Statistics

Table 2 lists the math scores of junior high students in their 7th and 9th grades and the difference between the 7th and 9th grades under different cramming statuses as defined above. We can see that around 60% (i.e., 1,110/1,836) of the students in the sample attended cram schools under the broadest definition of cramming statuses. Table 2 also shows that students who did not engage in cramming performed badly in terms of the differences in math scores between their 7th and 9th grades (-1.529), relative to students who went to cram schools in their 7th or 8th grades. Students participating in cram schools in both their 7th and 8th grades revealed a great improvement in their math test scores (0.979), suggesting that constant cramming might be beneficial to math performance. There is a negative difference in scores between the 7th and 9th grades for students with cramming activities in the 7th grade only, while the improvement is (positively) the largest for cramming in the 8th grade only. This may imply that the effect of last minute intensive learning works efficiently. Of course, it is noted that these figures are simply descriptive and that no other covariates are controlled. Thus, the preliminary inspection can not be viewed as causal.

Sample means of pupils' demographics are also listed in Table 2, where the parents' education level, household income, cramming history in elementary schools, self-expected years of schooling, and parents-expected years of schooling exhibit slightly higher figures for students involved in more cramming activities than students who are not. The parents' marital status for pupils engaged in cramming activities is more likely to be that they are married. Other characteristics are not significantly different between cramming and non-cramming statuses.[13]

3.2 Coaching Effects

We first conduct the OLS estimation as a benchmark to evaluate the coaching effect, which is done by checking whether the difference in the test scores between the 7th and 9th grades is associated with attending cram schools either in the 7th or 8th grade or both. Column (4) of panel (A) in Table 3 shows that there does exist a coaching effect, i.e., cramming would significantly improve the NCE math test scores by 2.636.

To implement the propensity score matching method, the following pre-treatment variables are adopted to construct the propensity score (i.e., by estimating a probit model to determine whether or not the student will attend cram schools): parental educational levels, parental (educational) expectations, household income, whether the student is attending a private school, school location, whether the student attended cram schools in elementary school (previous coaching experience), whether the class is a high ability class, whether the student is reviewing course materials, whether the student is easily distracted, whether math is troublesome to the student, and the parents' marital status.[14] We impose the common

[13]Sample means of pupils' demographics based on the third-wave TEPS data are reported in Table 4.

[14]The Probit regression results are available from the authors upon request.

support restriction to improve the matching quality. In addition, to ensure the reliability of the matching method, the balancing property that, conditional on $p(X)$ the observable characteristics are independent of the treatment status, has been tested during our matching process.

Our estimation results are presented in Table 3, which indicates that the causal effect of coaching math is significant if junior high-school students have attended cram schools owing to the increased NCE scores of 2.638 (column (5) of panel (A) in Table 3),[15] which is very close to the coaching effect based on the OLS method.

If we change the definition of cramming as implying that a student is involved in cramming activities in both the 7th *and* 8th grades (see panel (B) in Table 3), the causal effect of cramming is even higher, i.e., NCE scores of 3.060 (2.806 based on OLS results) that are higher than those of students who have never been to cram schools. Our results in panels (A) and (B) of Table 3 basically confirm the findings of previous studies (e.g., Becker, 1990; Egan and Bunting (1991); Stevenson and Baker, 1992; Powers and Rock, 1999) that coaching is effective in learning.

3.3 Coaching Effects by Timing of Attendance

We now try to evaluate the coaching effects based on the timing of attendance, which can be done by separating students into two groups (i.e., in the 7th grade only and in the 8th grade only) based on the timing of engaging in cram schooling.

The result in column (5) of panel (D) in Table 3 shows that cramming in the 8th grade only compared to not cramming at all would significantly increase the NCE score by 3.093 while the benefit from cramming in the 7th grade would only (insignificantly) increase the NCE score by 0.709.[16] That is, attending cram schools in the 8th grade, which is closer to the date of the test, is more effective than doing so in the 7th grade. The effort made two years before can not be carried over to the performance in the present math test, while it could be in the case of a student engaging in cram schooling one year before. Our finding implies that the best strategy for the budget-limited parents is to send their children to cram schools for intensive learning in the 8th grade rather than earlier in the 7th grade, in order to enhance their math scores in the 9th grade.[17] A final remark is that the amount of coaching may not be positively associated with the math scores, which can be reflected in panels (B) and (D) in Table 3, which suggest that math coaching in both the 7th and 8th grades does not result in better performance than coaching in the 8th grade only.

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[15] We report the estimated average treatment effects on treated by using the kernel matching method since it makes full use of the treated and control observations with different weights. Note that similar results are obtained based on the nearest neighbor matching method and are available upon request from the authors. We do not report them due to the fact that the size of the control sample is reduced dramatically from more than 700 to 464, 342, 157 and 239 under the four cramming statuses.

[16] We obtain the similar effects based on the OLS results (i.e., 1.119 for cramming in the 7th grade only and 3.485 for cramming in the 8th grade only). Please refer to column (4) of panels (C) and (D) in Table 3.

[17] The enhanced academic performance may also be reflected in the senior high-school entrance exam in the 9th grade by increasing the probability of entering prestigious a senior high school.

3.4 Robustness Check

In this subsection, we first list the summary statistics of the demographics of pupils based on the third-wave (2005) TEPS data in Table 4. Compared to Table 2, which is based on the first-wave (2001) data, the mean (observed) characteristics (e.g., school location, parents' marital status, household income, parents' education levels,...,etc.) in Table 4 are fairly stable in the sense that the observed confounding factors (both time-variant and time-invariant variables) do not reveal a significant fluctuation. In order to perform a robustness check of our finding, we then implement the propensity score matching method by replacing the pre-treatment variables with those based on the third-wave data (i.e., characteristics obtained in 2005). The results reported in Table 5 show that the general coaching effect is still significant (see panels (A) and (B)) and that the coaching effect based on the timing of attendance on NCE math scores really matters (see panels (C) and (D)). It is also noted that the magnitude of the coaching effects in Table 5 is quite close to that exhibited in Table 3.

4 Conclusion

Even though there are some studies on the positive effect of cram schooling, unfortunately, there is rather less discussion in previous studies on the impact on academic performance of the timing in terms of attending cram schools. The decision regarding the timing of engaging in such shadow education is crucial for family resource allocation, especially for parents constrained by a limited budget. We take advantage of the data set, the Taiwan Education Panel Survey, which keeps track of the students every two years, to evaluate the coaching effect during the period from 2001 to 2005. Using multiple regression analysis to uncover the causal effect of cramming on academic performance may give rise to the endogeneity problem. We then adopt the propensity score matching method to estimate the causal effect of cram schooling on math learning as well as the issue of the timing decision. We first confirm that the causal effect of cram schooling for math learning is significant using the data for junior high-school students in Taiwan. Secondly, our main finding suggests that the best strategy for the budget-constrained parents is to send their children to cram schools for intensive learning in the 8th grade rather than earlier in the 7th grade, in order to enhance the scores for math tests taken in the 9th grade. This result may provide some hints for a family's allocation of resources to shadow education. Finally, the sensitivity check confirms that our empirical finding is robust by replacing the pre-treatment variables from the first-wave for the propensity score matching method with the ones from the third-wave TEPS data.

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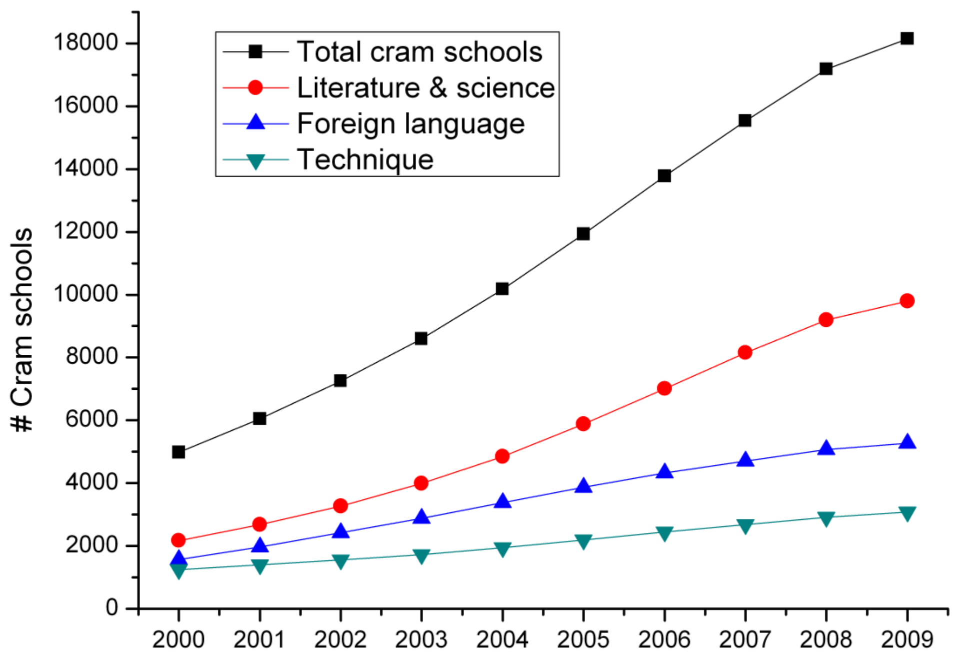

Figure 1: Number of cram schools in Taiwan for 2000-2009

Table 1: Description of Variables

Variables	Variables Description
Household income	Monthly income in 10,000 New Taiwanese Dollars.
School location	A dummy variable indicating whether the school is located in a rural area.
Parents' education level	The years of parental education levels.
Cramming in elementary schools	A dummy variable indicating whether a student has ever participated in cram schools in the 4th, 5th or 6th grades.
Self-assessed ability	A categorical variable of students' self-assessed future educational degree, indicating that he/she would be capable of finishing junior high school, senior high school, college, graduate programs or is unclear.
Self-expected education level	The years of self-expected education level.
Parent-expected education level	The years of parents' educational expectations for a student.
Private school	A dummy variable indicating whether a student attends a private school.
Parents' marital status	A dummy variable indicating whether the parents are in a married status.
Class grade is good*	Class average grade is good.
Discuss homework*	Classmates often discuss homework or study together.
Discuss entrance exam*	Classmates often discuss issues about the entrance examination.
Never distracted*	Never let anything distract doing homework.
Review course materials*	Always review course materials after school.
Solve difficult problems*	Always try to solve difficult problems in learning.
Math is a headache*	Math is always a headache.

Note: * indicates that the corresponding variable ranges on a scale from 1 to 4 with 1 representing the strongest agreement and 4 representing the weakest agreement, respectively.

Table 2: Sample Mean of NCE Math Scores and Pre-treatment Variables for Different Cramming Statuses Using the First-wave (2001) TEPS Data

	Cramming statuses				
Variables	7th or 8th	7th & 8th	7th only	8th only	No cram
7th grade NCE math scores	50.313	53.421	46.639	46.450	49.582
9th grade NCE math scores	51.280	54.400	46.186	48.263	48.052
7th & 9th grades score differentials	0.967	0.979	-0.453	1.814	-1.529
School location	0.030	0.021	0.063	0.026	0.045
Household income	6.365	6.420	6.231	6.339	6.180
Parents' education level	13.045	13.152	12.921	12.910	12.868
Cramming in elementary schools	0.799	0.854	0.732	0.732	0.646
Self-assessed ability (junior high)	0.030	0.023	0.037	0.039	0.029
Self-assessed ability (senior high)	0.132	0.110	0.179	0.148	0.165
Self-assessed ability (college)	0.494	0.502	0.442	0.510	0.494
Self-assessed ability (master)	0.196	0.226	0.174	0.152	0.172
Self-assessed ability (unclear)	0.148	0.139	0.168	0.152	0.139
Self-expected education level	16.492	16.636	16.268	16.345	16.285
Parent-expected education level	16.560	16.738	16.347	16.342	16.408
Private school	0.112	0.113	0.074	0.132	0.171
Parents' marital status	0.927	0.938	0.905	0.919	0.916
Class grade is good	2.345	2.333	2.463	2.297	2.348
Discuss homework	2.094	2.089	2.153	2.068	2.088
Discuss entrance exam	2.695	2.715	2.674	2.668	2.701
Never distracted	1.988	1.977	2.016	1.994	1.985
Review course materials	2.230	2.236	2.189	2.242	2.259
Solve difficult problems	1.874	1.826	1.889	1.958	1.860
Math is a headache	2.393	2.487	2.379	2.216	2.314
Sample sizes	1,110	610	190	310	726

Table 3: OLS and Causal Effects of Cramming for Math across Different Timings with Pre-treatment Variables Using the First-wave (2001) TEPS Data

Cramming Statuses	Number of Treated obs.	Number of Control obs.	OLS Results	Causal effects on treated
(1)	(2)	(3)	(4)	(5)
(A) 7th or 8th	1,110	726	2.636***	2.638***
			(0.776)	(0.760)
(B) 7th and 8th	610	703	2.806***	3.060***
			(0.903)	(0.908)
(C) 7th only	190	700	1.119	0.709
			(1.264)	(1.239)
(D) 8th only	310	701	3.485***	3.093***
			(1.050)	(1.015)

Notes: Standard errors are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4: Sample Mean of NCE Math Scores and Pre-treatment Variables for Different Cramming Statuses Using the Third-wave (2005) TEPS Data

	Cramming statuses				
Variables	7th or 8th	7th & 8th	7th only	8th only	No cram
7th grade NCE math scores	49.971	53.348	44.904	46.651	48.239
9th grade NCE math scores	50.890	54.263	45.246	47.922	46.464
7th & 9th grades score differentials	0.919	0.915	0.342	1.271	-1.775
School location	0.033	0.018	0.077	0.033	0.059
Household income	6.446	6.650	5.891	6.393	6.342
Parents' education level	13.119	13.502	12.655	12.678	12.628
Cramming in elementary schools	0.809	0.859	0.732	0.762	0.654
Self-assessed ability (senior high)	0.037	0.025	0.042	0.059	0.058
Self-assessed ability (college)	0.437	0.406	0.486	0.464	0.444
Self-assessed ability (master)	0.229	0.241	0.239	0.201	0.191
Self-assessed ability (phd)	0.130	0.161	0.099	0.092	0.143
Self-assessed ability (unclear)	0.164	0.167	0.127	0.180	0.162
Self-expected education level	18.356	18.674	18.141	17.887	18.061
Parent-expected education level	17.793	18.174	17.239	17.406	17.401
Private school	0.280	0.254	0.303	0.314	0.329
Parents' marital status	0.884	0.893	0.908	0.854	0.855
Class grade is good	2.337	2.328	2.458	2.280	2.338
Discuss homework	2.049	2.054	2.070	2.029	2.067
Discuss entrance exam	2.637	2.656	2.570	2.640	2.693
Never distracted	1.941	1.940	1.958	1.933	1.981
Review course materials	2.180	2.172	2.148	2.213	2.266
Solve difficult problems	1.855	1.824	1.887	1.895	1.857
Math is a headache	2.366	2.482	2.296	2.188	2.294
Sample sizes	829	448	142	239	538

Table 5: OLS and Causal Effects of Cramming for Math across Different Timings with Pre-treatment Variables Using the Third-wave (2005) TEPS Data

Cramming Statuses	Number of Treated obs.	Number of Control obs.	OLS Results	Causal effects on treated
(1)	(2)	(3)	(4)	(5)
(A) 7th or 8th	829	533	2.671***	2.626***
			(0.880)	(0.888)
(B) 7th and 8th	448	513	2.710***	2.891***
			(1.107)	(0.975)
(C) 7th only	142	510	1.859	1.132
			(1.460)	(1.294)
(D) 8th only	239	532	3.179***	2.849***
			(1.197)	(1.116)

Notes: Standard errors are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.