Class Attendance and Exam Performance: A Randomized Experiment*

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Abstract

The study of determinants of a college student's academic performance is an important issue in higher education. Among all factors, whether or not attending lectures affects a student's exam performance has received considerable attention. In this paper, we conduct a randomized experiment to study the average attendance effect for students who have chosen to attend lectures, which is the so-called the average treatment effect on the treated in program evaluation literature. This effect has long been neglected by researchers when estimating the impact of lecture attendance on students' academic performance. Under the randomized experiment approach, least squares, fixed effects, and random effects models all yield similar estimates for the average treatment effect on the treated. We find that, class attendance has produced a positive and significant impact on students' exam performance. On average, attending lecture corresponds to a 7.66% improvement in exam performance.

Keywords: class attendance, exam performance, random experiment

JEL code: A22, I21

I. Introduction

The study of determinants of a college student's academic performance is an important issue in higher education. Among all factors, whether or not attending lectures and classroom discussions affects a student's exam performance has received considerable attention. In light of the importance of the attendance effect, many researchers have explored the impact of a student's class attendance on his or her exam performance. Most studies find that attending lectures yields a positive and significant impact on exam performance (Anikeeff, 1954; Schmidt,1983; Jones,1984; Buckalew, *et al*., 1986; Brocato, 1989; Park and Kerr, 1990; Van Blerkom, 1992; Romer, 1993; Gunn,1993; Durden and Ellis, 1995; Devadoss and Foltz,1996; Marburger, 2001; Bratti and Staffolani, 2002; Dolton, *et al*., 2003; Kirby and McElroy, 2003; Rodgers, 2001; Rocca, 2003; Stanca, 2006; Lin and Chen, 2006).

The investigation of the attendance effect is indeed an estimation of the treatment effect in policy evaluation. In the program evaluation literature, two kinds of treatment effects are frequently mentioned. They are the average treatment effect and the average treatment effect on the treated. In the application of lecture attendance, the average treatment effect refers to the expected effect of attendance on academic performance for a randomly drawn student from the population. The average treatment effect on the treated refers to the mean attendance effect for those who actually participated (or not participated) in the classroom.

Literature is prolific in the area of the exploration of the average treatment effect when estimating the impact of a student's class attendance on his or her exam performance. In the estimation of the average treatment effect, it is of particular note that whether or not students choose to attend classes is an endogenous choice. Therefore, the estimated coefficient of attendance will suffer from the endogeneity bias and become inconsistent if researchers fail to take into account the sample selection issue. In order to remedy the endogeneity bias problem, econometric models including instrumental variable (IV), proxy variable and panel data methods are used to obtain consistent estimates in prior research (see Stanca (2006) for more details).

In stark contrast, existing studies in the area of attendance effect has not examined the average treatment effect on the treated. As discussed above, the average treatment effect is the expected effect of treatment on a randomly drawn student from the population while the average treatment effect on the treated measures the average benefits a student could receive given that he or she attends lectures. Most researchers focus on the estimation of the average treatment effect since the issue of whether or not to make attendance compulsory has received great attention in higher education. However, in the investigation of the attendance effect, we also want to evaluate the lecture participation benefits for students who actually choose to attend classes. This is similar to the example of job training program; what researchers and policymakers want to know is the impact of job training on labor outcomes for program participants but not for people from the population who probably would never be eligible for such programs. Hence, to complement current attendance effect literature, the focus of this paper is to investigate the average treatment effect on the treated.

One difficulty in the estimation of the average treatment effect on the treated arises from finding the desired counterfactuals. In this case, we will need to estimate what would have been the grades had the students not attended the class for those who actually do participate in the classroom. One way to circumvent the problem of finding desired counterfactual is to run a randomized experiment.

Burtless (1995) and Heckman and Smith (1995) both discuss advantages and disadvantages of social experiments. The foremost advantage of controlled experimentation is that the random assignment provides us with the clear causal link between treatment and outcome. In non-experimental data, it is usually not easy to tease out the causality between treatment and outcome. Random assignment also eliminates systematic correlation between treatment status and participants' observed or unobserved characteristics. In addition, experimentation is simple to understand to social scientists and policymakers. Some disadvantages of experimentation include expensive costs, ethical issues of experimentation with human beings, limited duration, attrition and interview non-response, partial equilibrium results and program entry effects.

In this study, we propose and implement a randomized experiment to estimate the average treatment effect on the treated. This paper will provide useful insights on the issue of the average treatment effect on the treated in the application of class attendance. Our empirical results demonstrate that least squares model will provide a consistent estimator under the randomized experiment. Class attendance has produced a positive and significant impact on students' exam performance. On average, attending lectures corresponds to a 7.66% improvement in exam performance.

The details of the random experiment will be discussed in the next section. In section III, the statistical models will be presented. In section IV, the data used for this study will be examined. The estimation results are reported in Section V, and the conclusion is summarized in Section VI.

II. The Random Experiment

The main goal here is to construct a random experiment to estimate the average treatment effect on the treated. The following notation is similar to the ones in Heckman and Smith (1995).

Y_1: grade outcomes associated with attending the lecture

Y_0: grade outcomes associated with not attending the lecture

$d = 1$, attending the lecture; $d = 0$, not attending the lecture

What we are interested in is the mean impact of attending lectures on exam performance for students who choose to attend classes. The average treatment effect on the treated can be shown below:

$$E(Y_1|d=1) - E(Y_0|d=1) \quad (1)$$

In order to estimate the average treatment effect on the treated, we need to know what would have been the grades had the students not attended the class. This implies that we will need an estimate for $E(Y_0|d=1)$ because it is unobserved by researchers. In general, $E(Y_0|d=0)$ can not be used as a proxy for $E(Y_0|d=1)$ since students who choose not to attend lectures might be different from those who choose to attend classes in many ways such as the unobserved individual intelligence and motivation. As a result, the selection process to attend or not to attend classes might become an issue and it will bias our results if we use $E(Y_0|d=0)$ to replace $E(Y_0|d=1)$.

Our main focus then is to construct a randomized experiment to solve the problem of selection bias. The goal is to generate an experimental group of students who would have participated but were randomly denied access to the treatment. By doing so, we could use this randomly selected group to be our control group and obtain their responses as the desired counterfactuals, $E(Y_0|d=1)$.

Here is how the randomized experiment works. The instructor taught the same course in two sections, section A and section B, in the spring semester of 2005. The course, Public Finance, is a required course for all junior students who major in Industrial Economics at Tamkang University in Taiwan. Students are allowed to register in any of these two sections[1]. At each class meeting, the same PowerPoint presentation is used in both sections, and the lecture slides are posted on the course web site after each class meeting. During the sample semester, the instructor randomly selects the dates, sections, and some materials/topics to cover or not to

[1] The characteristics of students in both sections are fairly similar. This can be shown in Table 3.

cover in only one section. However, students are told to be responsible for those materials/topics shown in the slides including the ones skipped by the instructor. This implies that materials/topics not covered by the instructor might appear in the two exams, and students will need to prepare and study those materials by themselves to be able to answer corresponding exam questions. In this study, about 10% of the exam questions were not covered by the instructor but yet appeared in the exams.

Let $d^* = 1$ denote the students who would participate in a lecture in the presence of random assignment, and $d^* = 0$ for everyone else. Also, let $r = 1$ denote the group of students who are randomly assigned to the treatment group for particular corresponding exam questions (i.e. the materials/topics corresponding to exam questions have been covered by the instructor), and $r = 0$ denote the group of students who are denied access to the treatment for particular corresponding exam questions (i.e. the materials/topics corresponding to exam questions have been randomly skipped by the instructor).

By introducing variables d^* and r, we can re-write equation (1) as

$$E(Y_1|d^* = 1, r = 1) - E(Y_0|d^* = 1, r = 1), \qquad (1')$$

where $d = 1$ is replaced by $d^* = 1, r = 1$. As mentioned above, the instructor randomly selects the dates, sections, and materials to cover or not cover. Also, when some materials are skipped in the lectures, students are asked to study the materials by themselves. They are told again about this information in their last class meeting before each exam. Thus, we could reasonably expect that

$$E(Y_0|d^* = 1, r = 1) = E(Y_0|d^* = 1, r = 0). \qquad (2)$$

$E(Y_0|d^* = 1, r = 0)$ is the expected grades for students who choose to attend lectures but do not actually get the *treatments* since some materials/topics are randomly skipped for corresponding exam questions. The original problem is that we cannot observe $E(Y_0|d^* = 1, r = 1)$ in (1').

$E(Y_0|d^* = 1, r = 1)$ is the average grades that would have been obtained had students not attended the lecture. This partial observation issue is a common problem in estimating the average treatment effect on the treated. By running the randomized experiment, we can now observe $E(Y_0|d^* = 1, r = 0)$ and use it as a replacement for $E(Y_0|d^* = 1, r = 1)$. Hence, by using equation (2), the average treatment effect on the treated can be shown below:

$$\begin{aligned} E(Y_1 - Y_0|d = 1) &= E(Y_1 - Y_0|d^* = 1, r = 1) \\ &= E(Y_1|d^* = 1, r = 1) - E(Y_0|d^* = 1, r = 1) \\ &= E(Y_1|d^* = 1, r = 1) - E(Y_0|d^* = 1, r = 0) \qquad (3) \end{aligned}$$

Thus, randomization serves as an instrumental variable by creating variations among students who choose to attend lectures, because some of them do receive the treatment randomly while some of them do not receive the treatment. In so doing, we will be able to estimate the average treatment effect on the treated accurately.

III. Statistical Models

In prior research, various econometric techniques including IV, proxy, and panel data models are usually used to remedy the endogeneity bias problem when estimating the average treatment effect. This paper sheds lights on the estimation of the average treatment effect on the treated by employing a randomized experiment. Under our randomized experiment, the mean outcomes of the experimental treatment group and the control groups provide estimates of the average treatment effect on the treated without getting into the trouble of sample selection bias.

This study uses a micro level data to explore the impact of a student's attendance on his or her exam performance. We use the following linear function to describe the relationship between students' exam performance and various input variables for learning.

$$y_{ij} = \beta x_{ij} + \eta r_{ij} + \alpha_i + \varepsilon_{ij}, \qquad i = 1, 2, \ldots, I, j = 1, 2, 3, \ldots, J \qquad (4)$$

I is the total number of students and J is the total number of exam questions. Y_{ij} corresponds to student i's exam performance on question j; x_{ij} is student i's set of observed inputs in learning question j. β represents the student input effect vector. r_{ij} is equal to one if student i attends the lecture when question j is covered. η is the attendance effect. α_i represents student i's time-invariant individual effect and ε_{ij} is the random disturbance term.

To estimate the average treatment effect on the treated (i.e. η), Least Squares (LS), Fixed Effects (FE) and Random Effects (RE) models will be employed. In this paper, we employ a linear probability model instead of a nonlinear probit model when estimating the individual effects. The main reason for doing so is that we are concerned about the incidental parameters problem in a typical nonlinear panel model (see Woldridge (2002) and Greene (2003) for details).

The estimation results of LS, FE and RE models are all listed for the use of comparisons. Under the experimental design, we would expect that all three models produce consistent estimators. By the definition of a randomized experiment, the treatment is randomly assigned within the estimation sample and will not be correlated with x_{ij} , α_i and ε_{ij}. This implies that LS estimation of the attendance effect can produced consistent result. Also, LS, FE and RE will produce similar estimates and all these three are consistent estimators.

IV. Data

We conduct a survey of 114 students who attended the Public Finance course at Tamkang University in Taiwan in the Spring of 2005. All students who major in Industrial Economics are required to take this course in their third-year of study. The students are in two separate sections. There are 67 students in one section, and 47 students in the other section. Attendance is recorded at each class meeting during the sample semester. There are 12 2-hour class meetings in addition to two exams and one project presentation during the sample period.

Students' demographic variables are collected form the survey distributed in the very first class of the sample semester. They include students' gender, average grades before taking this course, living arrangement and family economic condition. Also, the commuting time between students' apartment and school, and the working hours for each student are recorded. Moreover, two questions: hours students spent preparing for the exam and hours they spent studying every week, are asked when students took their midterm and final exams. Table 1 reports the summary statistics of students' characteristics.

In this paper, the dependent variable is a binary variable indicating students' exam performance. 50 multiple choice questions are asked in the midterm exam while 57 multiple choice questions are asked in the final exam. There are 12,028 observations which come from 114 students and their responses to the 107 exam questions[2]. We assign 1 to the binary variable if students answer the exam question correctly; otherwise the binary variable is 0.

The binary variable, *Actual Attendance*, is coded as 1 if students have attended the lecture in which the class material covered that day was relevant to the corresponding exam question, i.e. d_{ij} = 1 as discussed in the random experiment section. *Actual Attendance* is coded as 0 if students miss the class that day, i.e. d_{ij} = 0 as discussed in the random experiment section.

Among students who have attended lectures, we create a binary variable, *Experimental Attendance*. *Experimental Attendance* is coded as 1 if students have attended the lecture and the instructor has taught the material in that lecture, i.e. d^*_{ij} = 1 and r_{ij} = 1 as discussed in the random experiment section. *Experimental Attendance* is coded as 0 if students have attended the lecture but the instructor has randomly choose not to cover some materials for corresponding exam questions in that lecture i.e. d^*_{ij} = 1 and r_{ij} = 0 as discussed in the random experiment

[2] There are two students missing the final exam (57*2), and some questions are not answered by some students (56). So 114 * 107 – 57*2 - 56 = 12,028.

section.

Table 2 reports the means and standard deviations of students' actual attendance, experimental attendance, and their exam performance by students' demographic variables. The average actual attendance rate is about 91% which is higher than that in some previous studies (Romer (1993), Margurger (2001)). It is worth noting that the sample course, Public Finance, is a required course for students in their junior year. In addition, students are more likely to attend lectures when they are in their junior and senior years as pointed out by Rocca (2003). Therefore, a 91% class attendance rate seems reasonable. If we further restrict our sample to students who have chosen to attend lectures, we find that the experimental attendance is about 92%.

V. Estimation Results

Table 4 presents the estimation results for the average treatment effect. In this regression model, the independent variable is a binary variable indicating whether or not students answer the exam question correctly. The dependent variables include *Actual Attendance*, exam question dummies and individual time-invariant dummies. The number of observations is 12,028 in this case. The coefficient of *Attendance* in the panel linear probability model is about 4.32%, and it is about 7.03% in the least squares model. Thus, after controlling for individual unobserved characteristics, the consistent fixed effects estimator obtains a much smaller estimate on the attendance effect. Generally, our average treatment effect estimation results are comparable to prior studies. For instance, Stanca (2006) also finds that the OLS estimates overestimate the impact of attendance on exam performance.

Table 5 provides the estimation results for the average treatment effect on the treated. We restrict our sample to those students who have chosen to attend lectures. The sample size is 10,919 in this case. In this model, the independent variable is a binary variable indicating whether or not students answer exam questions correctly. The dependent variables include *Experimental Attendance*, exam question dummies and individual time-invariant dummies.

The principle finding of Table 5 is that the coefficients of *Experimental Attendance* in LS, FE ad RE models are almost the same. As mentioned earlier, randomization acts an instrument variable, and simply running the least square models will give us a consistent estimator. Hence, as we expected, LS, FE and RE models all produce similar results in the estimation of the average treatment effect on the treated under our randomized experiment. We find that, among students who choose to attend lectures, attending lectures yields a positive and significant impact on students' exam performance. On average, attending lectures corresponds to a 7.66% improvement in exam performance.

From Tables 4 and 5, we also find that the average treatment effect is lower than the average treatment effect on the treated. Our results suggest that the mean attendance effect for the population of students who choose to attend classes is greater than the mean attendance effect when students are randomly selected to attend lectures. This finding seems reasonable since we would expect that students who decide to attend lectures should or might have a higher return from attending classes than the ones who are randomly selected to attend lectures.

Some might be concerned about issues regarding the random assignment of treatment in this study. For instance, our estimation results may still suffer from some biases since students might expect that materials not covered by the instructor will be less likely to appear in the exams even though they are told to be responsible for those skipped materials in the exams. In order to examine whether students' perception might become an issue and bias our results, we further divide our sample into two sets: the midterm exam sample and the final exam sample.

If students think that materials not covered by the instructor are less likely to appear in the exam, we would expect to see different attendance impact on midterm and final samples. For example, in the midterm, if students assume that materials not covered by the instructor will not appear in the exam and they realize that they were wrong after the midterm, then they will pay the same attention to those skipped materials when preparing for the final exam. If this is the case, we would expect to see different results in the midterm and final samples. Otherwise, we would expect to find similar estimation results in the midterm and final exam samples.

Table 6 presents the estimation results for the average treatment effect on the treated in the midterm and final samples. In these two models, the independent variable is a binary variable indicating whether or not students answer exam questions correctly; the dependent variables include *Experimental Attendance*, exam question dummies and individual time-invariant dummies. It is of note that we find similar results in both cases. For the midterm exam, the average treatment effect on the treated is 7.51%; for the final exam, the average treatment effect on the treated is 7.91%. Taken together, we would not need to worry about the perception issue here. Moreover, this also assures us of the robustness of our estimation results.

VI. Conclusion

In this paper, a randomized experiment is designed to control for students' endogeneous class attending choices when exploring the impact of class attendance on exam performance. Under our randomized experiment, the mean outcomes of the experimental treatment and control groups provide estimates of the average treatment effect on the treated without getting into the trouble of sample selection bias.

Our estimation results show that, under the randomized experiment, simply running the least squares model will yield a consistent estimator. In addition, the LS, FE and RE models all produce similar estimates of the attendance effects. On average, attending lectures corresponds to a 7.66% improvement in exam performance for students who choose to attend lectures.

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Table 1: Summary Statistics

	Sample Size	%	Mean	Standard Deviation
All Students	114	1.000		
Gender				
Female	65	57.02		
Male	49	42.98		
Average Grade Before Entering the Course			72.047	7.7553
60-70	40	35.09		
70-80	47	41.23		
80-90	27	23.68		
Housing				
Live with Relatives	43	37.72		
Not Live with Relatives	71	62.28		
Family Economic Condition (1 to 5)			2.8596	0.5781
Poor (1)	4	3.509		
Below Average (2)	15	13.16		
Average (3)	89	78.07		
Above Average (4)	5	4.386		
Wealthy (5)	1	0.877		
Commute Time			29.355	32.425
less than 10 Minutes	37	32.46		
30-10 Minutes	41	35.96		
60-30 Minutes	7	6.140		
more than 60 Minutes	29	25.44		
Work Hours			6.9599	10.546
zero	65	57.02		
10-zero Hours	15	13.16		
20-10 Hours	15	13.16		
30-20 Hours	13	11.40		
more than 30 Hours	6	5.263		
Hours Studied Before the exam			8.6327	6.4431
Below 5 Hours	25	21.93		
5-10 Hours	58	50.88		
10-15 Hours	20	17.54		
Above 15 hours	11	9.649		
Hours Studied Every Week			1.5035	1.9138
Below 1 Hours	41	35.96		
1-2 Hours	47	41.23		
Above 2 hours	26	22.81		

Table 2: Actual Attendance, Experimental Attendance, and Exam Performance

	All Samples (N = 12,028)				Samples with Actural Attendance = 1 (N = 10,919)			
	Actural Attendance		Exam Performance		Experimental Attendance		Exam Performance	
	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
All Students	0.9088	0.0026	0.6313	0.0044	0.9198	0.0026	0.6347	0.0046
Gender								
Female	0.9261	0.0032	0.6387	0.0058	0.9165	0.0035	0.6404	0.0060
Male	0.8860	0.0044	0.6215	0.0067	0.9243	0.0039	0.6267	0.0071
Average Grade Before Entering the Course								
60-70	0.8425	0.0056	0.5914	0.0076	0.9209	0.0045	0.5950	0.0083
70-80	0.9296	0.0036	0.6259	0.0069	0.9177	0.0040	0.6256	0.0071
80-90	0.9654	0.0034	0.6978	0.0086	0.9225	0.0051	0.6996	0.0087
Housing								
Live with Relatives	0.9143	0.0032	0.6306	0.0056	0.9216	0.0032	0.6353	0.0058
Not Live with Relatives	0.8996	0.0045	0.6324	0.0072	0.9167	0.0043	0.6336	0.0076
Family Economic Condition								
Poor	0.8066	0.0191	0.6840	0.0226	0.9213	0.0144	0.7026	0.0247
Below Average	0.9296	0.0064	0.6258	0.0121	0.9210	0.0070	0.6232	0.0126
Average	0.9110	0.0029	0.6264	0.0050	0.9196	0.0029	0.6311	0.0052
Above Average	0.9132	0.0122	0.6811	0.0203	0.9196	0.0123	0.6722	0.0213
Wealthy	0.7925	0.0396	0.6887	0.0452	0.9048	0.0322	0.7024	0.0502
Commute Time								
less than 10 Minutes	0.9070	0.0047	0.6203	0.0079	0.9160	0.0047	0.6263	0.0082
30-10 Minutes	0.8974	0.0046	0.6252	0.0074	0.9225	0.0043	0.6260	0.0078
60-30 Minutes	0.9636	0.0069	0.6806	0.0171	0.9147	0.0105	0.6783	0.0175
more than 60 Minutes	0.9125	0.0051	0.6425	0.0086	0.9213	0.0051	0.6473	0.0090
Work Hours								
zero	0.9254	0.0032	0.6444	0.0059	0.9228	0.0034	0.6460	0.0061
10-zero Hours	0.9635	0.0047	0.6560	0.0119	0.9080	0.0074	0.6562	0.0121
20-10 Hours	0.8893	0.0078	0.6094	0.0122	0.9104	0.0075	0.6104	0.0130
30-20 Hours	0.8919	0.0084	0.5965	0.0132	0.9301	0.0073	0.6016	0.0140
more than 30 Hours	0.6745	0.0186	0.5849	0.0196	0.9209	0.0129	0.6047	0.0236
Hours Studied Before the exam								
Below 5 Hours	0.8671	0.0067	0.6124	0.0097	0.9203	0.0057	0.6089	0.0104
5-10 Hours	0.9098	0.0037	0.6397	0.0062	0.9190	0.0037	0.6468	0.0064
10-15 Hours	0.9304	0.0058	0.6309	0.0110	0.9324	0.0059	0.6368	0.0113
Above 15 hours	0.9456	0.0060	0.6325	0.0127	0.9086	0.0078	0.6276	0.0131
Hours Studied Every Week								
Below 1 Hours	0.9522	0.0037	0.6333	0.0084	0.9223	0.0048	0.6352	0.0086
1-2 Hours	0.9008	0.0041	0.6430	0.0066	0.9208	0.0039	0.6474	0.0070
Above 2 hours	0.8775	0.0056	0.6129	0.0083	0.9171	0.0050	0.6159	0.0088

Table 3: Sample Statistics for Section "A" and "B"

	Section A		Section B	
	Mean	Standard Deviation	Mean	Standard Deviation
Number of Students	67		47	
Male	0.4776	0.5033	0.3617	0.4857
Average Grade Before Entering the Cou	72.097	8.1414	71.909	7.3211
Live with Relatives	0.6716	0.4732	0.5532	0.5025
Family Economic Condition	2.8358	0.5928	2.8936	0.5608
Commute Time	29.750	32.351	29.213	33.098
Work Hours	5.5758	9.3002	9.1444	11.997
Hours Studied Before the exam	8.6119	6.4894	8.5333	6.4583
Hours Studied Every Week	1.5209	2.2242	1.3222	0.8691

Table 4: Estimation Results for the Average Treatment Effects

	Least Squares Method	Panel Linear Probability Model	
		Fixed Effects Model	Random Effects
Dependant Variable	Correctly Answer the Question (yes = 1, no = 0)		
Independant Variable			
Attendance	0.0703**	0.0432**	0.0519**
	(0.0142)	(0.0158)	(0.0151)
R-squares	0.2199	0.2473	.
F-value or X^2 value*	53.17**	50.04**	3435.06**
Sample Size	12,028	12,028	12,028

Note: "**" is at 5% significant level and "*" is at 10% significant level. White (1980) robust standard errors are in parentheses. Exam question dummies are used in all regressions. *: the F-values are reported in the Least Squares and Fixed Effects model

Table 5: Estimation Results for the Average Treatment Effect on Treated

	Least Squares Method	Panel Linear Probability Model	
		Fixed Effects Model	Random Effects
Dependant Variable	Correctly Answer the Question (yes = 1, no = 0)		
Independant Variable			
Attendance	0.0779**	0.0763**	0.0766**
	(0.0210)	(0.0202)	(0.0202)
R-squares	0.2228	0.2479	.
F-value or X^2 value*	48.69**	29.83**	3168.39**
Hausman Test (X^2_{107})		11.40	
Sample Size	10,919	10,919	10,919

Note: "**" is at 5% significant level and "*" is at 10% significant level. White (1980) robust standard errors are in parentheses. Exam question dummies are used in all regressions. *: the F-values are reported in the Least Squares and Fixed Effects model

Table 6: Estimation Results for the Average Treatment Effect on Treated by Midterm and Final Exams

	Midterm Exam			Final Exam		
	Least Squares Method	Panel Linear Probability Model		Least Squares Method	Panel Linear Probability Model	
		Fixed Effects Model	Random Effects		Fixed Effects Model	Random Effects
Dependant Variable	Correctly Answer the Question (yes = 1, no = 0)			Correctly Answer the Question (yes = 1, no = 0)		
Independant Variable						
Attendance	0.0751**	0.0761**	0.0756**	0.0791**	0.0715**	0.0738**
	(0.0393)	(0.0364)	(0.0363)	(0.0249)	(0.0246)	(0.0245)
R-squares	0.2176	0.2534	.	0.2261	0.2611	.
F-value or X^2 value*	39.81**	29.37**	1475.63**	56.62**	30.20**	1694.86**
Hausman Test (X^2_{50} or X^2_{57})		3.30			6.53	
Sample Size	5,247	5,247	5,247	5,672	5,672	5,672

Note: "**" is at 5% significant level and "*" is at 10% significant level. White (1980) robust standard errors are in parentheses. Exam question dummies are used in all regressions. *: the F-values are reported in the Least Squares and Fixed Effects model