行政院國家科學委員會專題研究計畫 成果報告

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行政院國家科學委員會補助專題研究計畫 ■ 成 果 報 告
□期中進度報告

（大學生上課出席與否對其考試表現之影響）

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執行單位：國立政治大學經濟學系

中　華　民　國　96　年　8　月　1　日

Abstract

College students' academic performance determination is an important issue in higher education. Among all factors, whether or not attending lectures affects students' exam performance has received considerable attention. In this paper, we conduct a randomized experiment to study the average attendance effect for students who choose to attend lectures, which is so-called 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, the results suggest that class attendance has a positive and significant impact on college students' exam performance. On average, attending lectures corresponds to a range of 9.4% to 18.0% improvement in exam performance for those who choose to attend classes. However, the improvement is only 5.1% using the empirical methodology of existing studies, which measure the overall average attendance impact.

Keywords: attendance, treatment effect, experiment, undergraduate

I. Introduction

Study of determinants of a college student's academic learning is an important topic in higher education research. One of the issues most educators are concerned about is the effect of teaching on a student's learning outcomes. Using exam performance as a proxy for learning performance, many researchers have studied the determinants of a college student's exam performance. Among all factors, whether or not attending lectures and classroom discussions affects a student's exam performance has received considerable attention; many researchers in different disciplines have explored the impact of a student's class attendance on his or her exam performance.

Researchers in the fields of education and psychology, by estimating correlations between exam performance and class attendance (Anikeeff, 1954; Brocato, 1989; Buckalew, *et al*., Gunn,1993; Jones,1984; Rocca, 2003; Van Blerkom, 1992), have generally found that a student's class attendance has a positive effect on his/her exam performance. Economists, like other social scientists, are also interested in class attendance effects. Most economists have used student-semester level data, and they have found results similar to those described in education and psychology literature: during a semester, the more lectures a student attends, the better overall grade he/she obtains (Schmidt, 1983; Jones, 1984; Park and Kerr, 1990; Romer, 1993; Durden and Ellis, 1995; Devadoss and Foltz, 1996; Dolton, *et al*., 2003).

Recently, some researchers linked the exam questions to students' attendance records and constructed a longitudinal type data set to investigate the class attendance effects (Marburger, 2001; Marburger, 2006; Rodgers, 2001; Stanca, 2006; Lin and Chen, 2006). In such data sets, researchers repeatedly observed the same student's responses to different questions, and also observed different students' responses to the same question. Hence, time invariant characteristics of both students and exam questions can be controlled in their statistical models. These rich data sets allow researchers to address some other interesting issues in addition to the attendance effects[1].

Attending a lecture can be viewed as a treatment to students, and thereby investigation of the attendance effect is indeed an estimation of treatment effect. In program evaluation literature, two kinds of treatment effects are frequently mentioned. They are "average treatment effect" and "average treatment effect on the treated". In application of lecture attendance, the average treatment effect refers to the expected effect of attendance on academic performance for a randomly drawn student. The average treatment effect on the treated, on the other hand, refers to the mean attendance effect for those who *actually* participated in the classroom.

For instance, in reality there might be two types of students, type A, those who choose to attend lecture regularly, and type B, those who are less conscientious about attending. To

[1] For example, Marburger (2006) studied the mandatory attendance policy effect and found that an enforced mandatory attendance policy significantly reduces absenteeism and improves exam performance. Lin and Chen (2006) incorporated the spillover effects from absenteeism in estimation of college students' academic performance and found a significant and positive effect of past cumulative attendance on exam performance.

simplify the story, η_A and η_B refer to the lecture attending effect for type A and type B students respectively. There is a good reason to believe that η_A and η_B are not equal, and, indeed, that η_A is larger than η_B. Type A students attend lecture more regularly; and this may imply that they obtain greater benefit from attending which makes their learning more effective.

In prior research, measures of the impact of lecture attending on students' performance are estimating a weighted average of η_A and η_B. This is so called average treatment effect in the program evaluation literature. It measures the average attendance effect for a student being randomly selected to receive the treatment (i.e. attend a lecture). Since the randomly selected student could be a type A or a type B student, so the effect is a weighted average of η_A and η_B. This weighted average attendance effect can also be a measure of the potential benefits for enforcing a mandatory attendance policy, since under the policy both type A and type B students are required to attend lectures. Thus, most researchers focus on 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, the estimation of the average treatment effect on the treated or the magnitude of η_A is not only interesting but also as important as the average attendance effect for the following reasons. Firstly, the average attendance effect on the attendees can be viewed as the actual output produced by the course or by the instructor, which deserves special attention. This idea is similar to the example of job training programs; what researchers and policy-makers really want to know is the impact of job training on the outcomes for program participants but not for an average person in the population.

Secondly, the comparison between the average attendance effect (i.e. weighted average of η_A and η_B) and the effect on the treated (i.e. η_A) is interesting and insightful. If a student decides to attend lectures regularly, it implies that the expected benefit of going to classes is greater than the opportunity costs. Therefore, given similar opportunity costs of attending lectures for type A and type B students, we would expect that, on average, the average weighted attendance effect is smaller than the effect on the treated. That is to say that the weighted average of η_A and η_B is smaller than η_A; and this implies that η_B is smaller than η_A. This hypothesis can be tested by estimating and comparing these two attendance effects. To complement the current attendance effect literature, the focus of this paper is to investigate the average treatment effect on the treated.

The main purpose of this paper is to conduct a randomized experimental approach to estimate the average attendance effect on the treated. Details of the randomized experiment will be discussed in the next section. In section III, data used for this study will be examined. In section IV, statistical models will be presented. Estimation results are reported in Section V and conclusion is summarized in Section VI.

II. The Randomized Experiment

The main goal here is to construct a randomized experiment to estimate the average attendance effect on the attendees. One difficulty in 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 the desired counterfactuals is to run a randomized experiment. The pros and cons of social experiments are detailed in Burtless (1995) and Heckman and Smith (1995)[2].

Under our experiment design, we randomly select some topics that are not lectured but are examinable. We know which students attended the lecture, so we can observe how their exam performance on questions corresponding to the randomly unlectured material. And then we compare their performance to the performance of those who attended the other class and did not miss the skipped material on the same questions. Hence, we get to measure the attendance effect for attendees.

It is of note that the treatment in this experiment is receiving lecture. This attendance effect can also be viewed as "the effect of omitted lecture material on learning," if the treatment is defined the other way around. For example, instead of defining "receive the lecture" as the treatment, we might define "forcing students skip some topics" as the treatment.

Below, we will discuss the theoretical basis of our experiment; 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 attendance effect on the attendees is shown below:

$$E(Y_1|d=1) - E(Y_0|d=1) \tag{1}$$

In order to estimate the effect, 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

[2] The foremost advantage of controlled experimentation is that the random assignment provides us with clear causal links between treatment and outcome. In non-experimental data, it is usually not easy to extract the causality between treatment and outcome. Random assignment also obliterates systematic correlation between treatment status and participants' observed or unobserved characteristics. In addition, controlled experimentation is simple to understand for social scientists and policymakers. Some disadvantages of controlled experimentation include high costs, ethical issues of experimentation with human beings, limited duration, attrition and interview non-response, partial equilibrium results and program entry effects.

attend classes in many ways, such as unobserved individual intelligence and motivation. As a result, the process of selecting 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 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, $E(Y_0|d=1)$. Ideally, the instructor can randomly select some students and asks them to leave the classroom at the beginning of each lecture. However, this approach comes with at least two major problems. Firstly, the instructor will have some difficulties in convincing the university officials to allow him or her to run such an experiment because asking students to skip lectures is something a university usually does not want to do. Secondly, perhaps the more problematic issue, students' decisions to attend (or not to attend) lectures might be altered, once students learn that there is a possibility of their being denied access to classes.

Due to the above two potential problems, we propose a different approach to estimate the counterfactuals. Here is how the randomized experiment works. The instructor taught the same course in two sections in the sample semester. At each class meeting, the same PowerPoint presentation is used in both sections and the lecture slides are posted on the course website after each class meeting. During the sample semester, the instructor randomly selects the dates, sections, and some materials/topics which would be covered in only one section but not in the other section. Notice that the lecture slides which are randomly skipped in one of the sections have to be taught in the other section. Consequently, we can observe and compare students' performance from receiving and not receiving the lecture slides.

In addition, students are told to be responsible for 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 the corresponding exam questions. In this study, about 8% of the exam questions were not covered by the instructor and yet they 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 exam questions (i.e. materials/topics corresponding to exam questions are covered by the instructor), and $r = 0$ denote the group of students who are denied access to the treatment for particular exam questions (i.e. materials/topics corresponding to exam questions are randomly skipped by the instructor).

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

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

where $d = 1$ is replaced by $d^* = 1$ and $r = 1$.

We could reasonably expect that

$$E(Y_0|d^* = 1, r = 1) = E(Y_0|d^* = 1, r = 0) \tag{2}$$

$E(Y_0|d^* = 1, r = 0)$ is the expected grades for students who choose to attend lectures but do not actually receive certain *treatments* since materials/topics corresponding to certain questions are randomly skipped. 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 the 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 attendance effect on the attendees can be shown as below:

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

Thus, randomization (i.e. $r = 1$ *or* $r = 0$) serves as an instrumental variable by creating variations among students who choose to attend lectures, because some of them receive the treatment (i.e. $r = 1$) while some of them do not (i.e. $r = 0$). In so doing, we will be able to estimate the counterfactuals for the attendees and obtain the average attendance effect on them accurately.

III. Data

We conducted a survey of 114 students who took the Public Finance course at a private university in Taiwan in the spring semester of 2005. All students who major in Industrial Economics are required to take this course in their third-year of study. Students are in two separate sections. There are 67 students in the first section and 47 students in the second section. Students can freely choose to register in either section. Both sections are taught by the same instructor, at different meeting times. One class meets at 3 p.m. and the other meets at 5 p.m. Also, the same PowerPoint presentation is used in both sections, and lecture slides are posted on the course website after each class meeting. There are 12 2-hour class meetings in addition to two exams and one project presentation during the sample period. The same exam questions are taken by all students in both sections at the same time. Attendance is recorded at each class meeting during the sample semester.

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[3]. We assign 1 to the binary variable if students answer the exam question correctly; otherwise the binary variable is 0.

There are two main independent variables, *Actual Attendance* (i.e. d^* in equation (3)) and

[3] There are two students missing the final exam (57*2), and some questions are not answered by some students (56). So 114 * (50+57) - (57*2) - 56 = 12,028.

Experimental Attendance (i.e. r in equation (3)). *Actual Attendance* is used to obtain the average attendance effect while *Experimental Attendance* is used to estimate the average attendance effect on attendees. 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. $d^* = 1$, as discussed in the random experiment section. *Actual Attendance* is coded as 0 if students miss the class that day, i.e. $d^* = 0$.

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 ($d = 1$) and the instructor has taught the material in that lecture ($r = 1$). *Experimental Attendance* is coded as 0 if students have attended the lecture ($d = 1$) but the instructor has randomly chosen not to cover materials corresponding to exam questions in that lecture ($r = 0$).

The average actual attendance rate is 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 choose to attend lectures, we find that the average experimental attendance is about 92%, which also implies that 8% of the lecture materials are randomly skipped.

Table 1 reports the percent correct on exam questions by students' attendance records and types of exam questions. The percent correct on exam questions are computed by two groups: attendees and non-attendees. The first column presents the percent correct of attendees' exam performance, and the second column presents the percent correct of non-attendees' exam performance. In addition, exam questions are divided by two types: type X and type Y. Type X exam questions correspond to materials covered in lecture. And type Y questions correspond to unlectured materials for some attendees.

The percent correct on type X questions for attendees is 64.6% and that for non-attendees is 63.2%; the difference is not significant. Namely, the average scores on type X questions are very similar between attendees and non-attendees. As for type Y questions, if they are covered in lecture, the percent correct on these questions for attendees is 62.7%. However, if these type Y question are randomly skipped for comparison purpose, the percent correct is 51.1%. That is to say when the attendees are randomly assigned to the control group and do not receive the lecture treatment, their average score is much lower at 51.1%. Thus, without controlling students' individual effects and exam question effects, the attendance effect on the attendees is about 11.6% (the difference between 62.7% and 51.1%). It is worth noting that non-attendees perform a fair low score on type Y questions and the percent correct is only 44.9%.

IV. Statistical Models

This study uses a micro level data to explore the average attendance effect for students who choose to attend lectures. We use the following probit model to describe the relationship between a student's exam performance and various learning input variables.

$$y^*_{ij} = \eta r_{ij} + \alpha_i + \gamma_j + \varepsilon_{ij}, \quad \text{and}$$

$$y_{ij} = \begin{cases} 1 \; if \; y^*_{ij} \geq 0 \\ 0 \; if \; y^*_{ij} < 0 \end{cases}, \qquad i = 1, 2, \ldots, I, j = 1, 2, 3, \ldots, J \tag{4}$$

I is the total number of students and J is the total number of exam questions. y_{ij} corresponds to student i's observed exam performance on question j, y^*_{ij} is the unobserved propensity to exam performance. r_{ij} is the *experimental attendance* which equals to one if student i attends the lecture when question j is covered; r_{ij} equals to zero if student i attends the lecture when question j is not covered. η is the attendance effect. α_i represents student i's time-invariant individual effect, γ_j represent question j's effect, and ε_{ij} is a random disturbance term.

We restrict our sample to attendees; and the parameter of interest in this study is η, the average attendance effect on the attendees. Both probit and probit with individual dummies models will be employed. The probit with individual dummies models will be called probit fixed effects models hereafter. 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, γ_j and ε_{ij}. This implies that probit estimation of the attendance effect will yield consistent results even though individual effects are not controlled in the probit model. Thus, we would expect that both probit and probit fixed effects models are consistent and produce similar estimates.

V. Estimation Results

Table 2 presents the estimation results for the average attendance effect (i.e. weighted average of η_A and η_B), and it replicates previous observational studies such as Marburger (2001, 2006) and Stanca (2006). To be consistent with prior research, both attendees and non-attendees are included in the analysis sample. In addition, observations corresponding to unlectured topics are removed form the sample. The number of observations is 11,097 in this case.

The first column reports estimation results of the probit model, and the second column reports estimation results of the probit fixed effects model. In both models, the dependent variable is a binary variable, indicating whether or not the students answer the exam questions correctly. Independent variables in the probit model include *Actual Attendance* and exam question dummies. In addition to these independent variables, individual time-invariant dummies are also used in the probit fixed effects model. Both the coefficients and marginal effects for the *Actual Attendance* variable are reported. Notice that marginal effects are evaluated at the sample means of the independent variables. Below we will mainly discuss the marginal effects results since it is more intuitive to interpret them.

From Table 2, we find that attendance has produced a significant and positive impact on students' exam performances. The marginal effect of *actual Attendance* in the probit model is 8.6% and it declines to 5.1% in the probit fixed effects model. Thus, after accounting for individual heterogeneity, we obtain a smaller attendance effect in the probit fixed effects model than in the probit model. This result is similar to that in previous research. For instance, Stanca (2006) found that least squares overestimate the impact of attendance on exam performance. In Stanca (2006), the average attendance effects range from 7.3% to 9% and the size of the attendance effect declines to 4% in the fixed effects model. Also, Marburger (2001, 2006) found that absenteeism increases the probability of answering the exam question incorrectly. Absenteeism effects range from 7.5% to 14.6% in Marburger (2001) and from 9% to 14% in Marburger (2006).

Table 3 presents the estimation results of the average attendance effect on the attendees under the randomized experiment setting, which is the main focus of this study. Firstly, we restrict our samples only to those observations with *actual attendance* equal 1. There are 114 students and the sample size is 10,919. In this case, we will obtain the average attendance effect on the attendees. In addition, in order to estimate the attendance effects for type A students who choose to attend lectures regularly (i.e. η_A), we use another three sets of analysis samples. The definitions of these samples are described below.

1. the attendees who never missed a lecture,
2. the attendees who never missed a lecture, or missed only one lecture, and
3. the attendees who never missed a lecture, or missed only one lecture, or missed only two lectures.

Among the 114 students, there are 48 students who never missed a lecture at all, and 76 of them missed fewer than 2 lecture. In addition, there are 99 students who missed fewer than 3 lectures. In these models, the dependent variable is a binary variable, indicating whether or not the students answer the exam questions correctly. Independent variables in the probit model include *Experimental Attendance* and exam question dummies. In addition to these independent variables, individual time-invariant dummies are also used in the probit fixed effects model.

There are two important findings in Table 3. Firstly, the marginal effects of *Experimental Attendance* in both probit and probit fixed effects models are nearly identical in all sets of analysis samples. For instance, the marginal attendance effects for the students who never missed any lecture are 18.0% in both models. The same finding is also held for the other three sets of analysis samples. As emphasized in the random experiment and the statistical model sections, randomization serves as an exogenous instrumental variable. Thus, whether time-invariant individual characteristics are controlled in the probit model or not, both probit and probit fixed effects models should yield consistent estimators.

Secondly, we find that the more frequent a student attends lectures, the greater the benefits he/she obtains from attending. Among students who attend lectures regularly, attending lectures yield a positive, significant, and larger impact on their performance for those who attend more often. For example, the average attendance effect for students who never missed any lecture is 18.0%, and it becomes 14.7% for attendees who missed fewer than two lectures. The attendance effect is 11.7% for attendees who missed fewer than three lectures. Lastly, for all attendees, the attendance effect declines to 9.4%. This interesting finding is intuitive and consistent with our prediction since students who have decided to attend lectures regularly may have a higher return from attending classes than those who are less likely to attend.

Comparing the estimation results in Table 2 and Table 3, we also find that the weighted average attendance effect, 5.0%, is much lower than the average attendance effect on the attendees which ranges from 9.4% to 18.0%. The results suggest that the mean attendance effect for students who choose to attend classes regularly (i.e. η_A) is greater than the mean attendance effect when students are randomly selected to attend lectures (i.e. weighted average of η_A and η_B). This finding is also consistent with our intuition because students who decide to attend lectures may produce a higher return from attending classes than those who are randomly selected to attend.

VI. Conclusion

This study contributes to literature on class attendance effects by using a randomized experiment to estimate the average attendance effect on the attendees. We conduct a classroom experiment to control for students' endogenous class attending choices and explore the impact of class attendance on exam performance. Our data set provides us with a great opportunity not only to replicate previous observational studies in estimation of attendance effect but also to clearly identify the causal link between attendance and exam performance in an experimental setting. Under our randomized experiment, the mean outcomes of the experimental treatment and control groups provide estimates of the average attendance effect on the attendees.

Our estimation results show that under the randomized experiment, simply estimating the probit model, without controlling for students' heterogeneity, still yields consistent estimates. In addition, probit and probit fixed effects models both produce similar estimates of attendance effects. On average, attending lectures corresponds to a range of 9.4% to 18.0% improvement in exam performance for students who choose to attend lectures. Moreover, the more frequent a student attends lectures, the greater the benefits he/she may obtain from attending. Lastly, the average attendance effect on the attendees is much larger than the average attendance effect. We find that the improvement is only 5.1% using the empirical methodology of existing studies, which measure the overall average attendance impact.

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Table 1: Sample Means of Exam Performance

(by Attendance Record and Type of Exam Questions)

		Attendees ($d^* = 1$)			Non-Attendees ($d^* = 1$)		
		Mean	Standard Deviation	Sample Size	Mean	Standard Deviation	Sample Size
Type X Questions	($r = 1$)	0.6459	0.0050	9224	0.6321	0.0163	878
Type Y Questions	For those attendees for whom this material was covered in lecture ($r = 1$)	0.6270	0.0162	893	0.4492	0.0347	207
	For those attendees for whom this material was NOT covered in lecture ($r = 0$)	0.5108	0.0174	826			

Note: Type X questions are the ones based on material covered in lecture for all attendees. Type Y questions are the rest of the questions (randomly skipped in either one of the sections).

Table 2: Estimation Results for the Average Attendance Effect

	Probit (with exam question dummies only)		Probit Fixed Effects (with both sets of exam and individual dummies)	
	Coefficients	Marginal Effects	Coefficients	Marginal Effects
Dependant Variable	Correctly Answer the Question (yes = 1, no = 0)			
Independant Variable				
Actual Attendance	0.2386**	0.0862**	0.1422**	0.0509**
	(0.0478)	(0.0173)	(0.0543)	(0.0194)
Sample Size	11,097		11,097	

Note: "**" is significant at 5%. White (1980) robust standard errors are in parentheses.

Table 3: Estimation Results for the Attendance Effects on Attendees

	Probit (with exam question dummies)				Probit Fixed Effects (with both sets of exam question and individual dummies)			
	Coefficients	Marginal Effects	Sample Size	Number of Students	Coefficients	Marginal Effects	Sample Size	Number of Students
Dependant Variable	Correctly Answer the Question (yes = 1, no = 0)							
Independant Variables								
Experimental Attendance								
Sets of Anslysis Samples								
1. The attendees who never missed a lecture	0.4689**	0.1800**	5,026	48	0.4717**	0.1802**	5,026	48
	(0.0951)	(0.0376)			(0.0972)	(0.0385)		
2. The attendees who missed fewer than two lecture	0.3832**	0.1466**	7,641	76	0.3825**	0.1455**	7,641	76
	(0.0774)	(0.0305)			(0.0789)	(0.0311)		
3. The attendees who missed fewer than three lectur	0.3065**	0.1165**	9,455	99	0.3067**	0.1169**	9,455	99
	(0.0699)	(0.0274)			(0.0712)	(0.0278)		
4. All Attendees	0.2474**	0.0935**	10,919	114	0.2509**	0.0943**	10,919	114
	(0.0656)	(0.0255)			(0.0669)	(0.0259)		

Note: "**" is significant at 5%. White (1980) robust standard errors are in parentheses.