"No Significant Distance" Between Face to Face and Online Instruction: Evidence from Principles of Economics

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Information technology has caused a revolution in higher education. Stand alone on-line courses and complete degree programs are now offered at many institutions. Virtual universities with entire curriculums offered through distance education via the world wide web have also appeared. This revolution in instructional technology has led researchers to question the efficacy of these new approaches, much like researchers questioned the use of television as a medium of instruction in past decades, or even earlier the mail. This paper describes a research project addressing the effectiveness of online education in the context of principles of economics courses offered at the college level.

We devised an experiment based on a comparison of matched face to face and online principles of economics courses offered at three different four-year institutions. This experiment focused on measuring and explaining differences in students learning between these two modes of instruction. We made no effort to quantify or examine student attitudes about their online learning experience. Many such studies have been conducted, and are described below in a section reviewing the literature on traditional and web-based instruction. Instead, we focused on documenting and explaining differences in student outcomes for these two alternative mediums of instruction.

Our results indicate that students in face-to-face sections scored better on the Test of Understanding College Economics (TUCE) than students in online sections. Self-selection into online classes was also an important issue. Failure to account for this selection leads to biased and inconsistent coefficient estimates in education production functions and may result in misleading inferences regarding "no significant difference" between online and face to face instruction. Indeed, we find that failure to account for the selection issue biases toward zero the differential between scores on the TUCE from students taking principles of economics face to face and those taking it online. The selection-corected differential is a statistically significant 3 to 6 fewer correct answers by online students compared to face to face students. However, an endogenous switching model finds that students who select into the online classes perform better than they would, all other things constant, in a face to face class. Underclassmen - freshmen and sophomores - are especially vulnerable to underperforming in online classes relative to how they would fare in a face to face class. For this reason, offering online principles of economics sections to freshmen and sophomores may not be pedagogically sound. The results also suggest caution in using the web to respond to on-campus physical plant limitations.

The next section discusses the literature and is followed by a section describing the survey instrument used to gather background information on the students in the courses. The third section describes the institutions where the courses were offered, the courses involved, and the data collected in this research. Section four addresses the empirical methodology and estimation issues that affect that methodology. Section five reports the results of the analysis and is followed by a brief conclusion.

Literature Review on Internet Technology Use

According to Becker and Watts (2001), Becker (1997) and Siegfried, Saunders, Stinar and Zhang (1996), most economists prefer the "chalk and talk" mode of instruction. Despite this preference, the use of technology, particularly the Internet and web-based learning, has increased in economics over the last few years. Although Sosin

(1997) found that economics faculty had access to the latest technology but did not incorporate it in their pedagogy, a recent survey by Blecha (2000) found a steady increase in the faculty use of the Internet in their courses over the last few years. Navarro (2000) and Coates and Humphreys (2001b) report similar increases in the offerings of cybereconomics classes. The well-attended sessions on pedagogical use of the Internet in national conferences, special conferences organized for the study of technology use in economic education such as the National Science Foundation, and the recent *Journal of Economic Education* sponsored conference on "Integrating Instructional Technologies in the Teaching of Undergraduate Economics" in 1998 provide additional evidence of interest in this area.

The increased use of the Internet in economic education has been attributed to its facilitation of both communication and information dissemination. Studies in education and communication technology comment on the potential of greater interaction between the instructor and the students, and the “hands-on” manner of learning new concepts.[1] Several textbooks in introductory economics now feature supplementary Internet tools, and have extensive web-sites to help communicate the information.[2] Goffe and Parks (1997) discuss the unlimited future possibilities for using technology and networks for teaching and augmenting every aspect of the economics curriculum.

[1] The studies include Bailey and Cotlar (1994), Boldt, Gustafson and Johnson (1994), Monahan and Dharm (1995), Kearsley, Lynch and Wizer (1995), Kuehn (1994), Manning (1996) Santoro (1994) and Zack (1995).

[2] These include Parkin (1997), Mankiw (1998), O’Sullivan and Sheffrin (1998). Web-sites of the leading publishers give information on other textbooks that incorporate the Internet.

While there is unequivocal evidence on the increased use of the Internet in economics courses, the evidence on its impact on student performance is far less conclusive. A few studies have investigated the issue and find mixed results. Gregor and Cuskelly (1994) find support for the hypothesis that students find value in electronic bulletin board communication, and Manning (1996) illustrates the beneficial use of e-mail to economics courses. Similarly, Coates and Humphreys (2001a) find that students in face to face classes who make greater use of course bulletin boards did significantly better on course exams than other students. Agarwal and Day (1998) devised an experiment in which student and instructor performances were compared across control groups that employ traditional teaching methods and test groups that contain the Internet-enhanced teaching methods. Their evidence shows a positive impact of the Internet on student retention and learning of economic concepts, attitudes towards economics, and perception of instructor effectiveness. Primont and Summary (1999a) report similar findings for attitudes and student performance. Agarwal and Day (2000) find that creative use of the Internet allows use of small class interactive techniques in larger classes, and has a beneficial impact on student grades. Interestingly, they find that women tend to benefit more from courses that use technology, thus offsetting some of the gender disadvantages they experience in traditional economics courses.

In contrast, Conrad (1997) found that, although Internet use increases enjoyment, there are no statistically significant gains observed in student performance. The same conclusion is reached by Talley (2000) for a wide variety of technology use in courses, including the Internet, remote televised lectures, streaming video, and electronic textbooks. In addition, literature from other disciplines has found similarly mixed results. Russell (2000a) compiled an impressive research bibliography on the "No Significant Difference" phenomena across pedagogical styles, and several of the articles linked on the website relate to comparisons between traditional and web-based courses. A comparable website [Russell (2000b)] on "Significant Difference" links to articles that find significant differences (positive and negative) across differential use of technology.

The above studies indicate that the "jury is still out" on the issue of the effectiveness of Internet use in economics courses. Since technology use often imposes significant learning costs on instructors, more research needs to be conducted on both the issue of whether such incorporation is indeed beneficial, and whether there are decreases in marginal costs that offset the high initial fixed costs.

Survey Design

This study assesses the benefits of online versus face to face instruction in principles-level economics classes. To make this assessment, we estimate education production functions for matched pairs of face-to-face and online principles of economics classes taught by the same instructors in the Fall 2000 semester at three institutions. The values for the inputs to the production function, socio-demographic characteristics of the students which capture their ability, their preparedness, and their previous experience with the material and with online education, were obtained via a survey. The survey, which was administered online to students both in classroom and online sections, took about nine months to design and implement. The design process was conducted entirely online via asynchronous e-mail discussions among the participants in the study. A copy of the survey is available upon request.

Two main issues arose during the design of the survey. First, we recognized the potential for self-selection bias as students choose whether to enroll in a distance learning section as opposed to a classroom section. Determining appropriate variables to control for this potential bias was a difficult problem. One control for this selection effect is the length of the student's commute to campus measured in minutes. Students who live on campus were directed not to answer this question. This instrument is not likely to be correlated with the student's performance, but it should affect the probability of selecting a distance learning section.[3] We also asked students about their previous experiences with web-based instructional techniques and if they had friends who had taken an online class at some point in the past. These variables served as instruments for the choice of online or face to face instruction.

The second major issue in the survey design phase centered around how to capture the data – as grouped responses from which students could choose or as free responses. The survey design used both types of questions to try to get the most reliable data possible.

The variables collected fall into four general, though not mutually exclusive, categories. These categories are student preparation or prior knowledge, student and family characteristics, student ability, and constraints. For example, to control for student preparation and prior knowledge, the survey asks about economics courses (high school and college) that students may have taken prior to the current course. Students

[3]One might argue that the length of the commute influences the severity of the time constraint facing the students. If a long commute reduces time available for studying, then it could influence the score on the measure of the outcome of the learning process.

were also asked about prior experience with the internet and in distance learning courses, and about their perceived ability in math. In addition, students took the Test of Understanding College Economics (TUCE) as a pretest.

Variables that addressing student and family characteristics were also collected. For example, questions asked about the student's age, race and gender, and about their parents' education. Student ability is addressed by the student's GPA, and his or her SAT scores. The ACT score of one student who did not take the SAT was converted to an SAT score using a transformation guideline used by the Admissions Office at UMBC.

Finally, the survey addressed the constraints facing the students. Questions asked about jobs and hours of work, about hours of course work, whether or not the student belonged to a fraternity or sorority, participated in intercollegiate athletics, had transferred, or was receiving financial aid. In addition, students were asked about their primary internet access.

The surveys were administered online to all students through a third-party polling service. There was some concern about the possibility of low response rates associated with an optional online survey, so instructors provided the students an incentive (extra credit) for completing the survey. This incentive appears to have worked as response rates were quite good. For Christopher Newport University the numbers are 31 of 36 face to face responses and 33 of 36 online responses for a total response rate of 89%. For SUNY-Oswego, 26 of 29 online students and 19 of 24 face to face students completed the survey, an 85% response rate. The response rate at UMBC is almost 96%, with 35 of 37 online students and 34 of 35 face to face students having completed the survey.

Initial plans for the study included collection of information on instructor effectiveness. This plan was problematic for several reasons, including a vast literature comparing student perceptions of instructor effectiveness between distance learning and classroom sections [see for example, Agarwal and Day (1998); Vachris (1997)]. The results of this literature are fairly well known and consistent: online economics students generally seem to "like" the course and the instructor at least as well if not better than classroom economics students. Finally, any systematic unobserved heterogeneity is captured in an institution-specific variable. While this variable captures a multitude of other influences that are institutionally specific, it also reflects instructor specific attributes.

Institutional and Course Descriptions

The institutions from which the students for this study are drawn are Christopher Newport University (CNU), State University of New York College at Oswego, and the University of Maryland, Baltimore County (UMBC). These institutions differ in many respects. CNU and UMBC are in fairly urban areas, with UMBC being in the suburbs of a large city. Oswego is located in a largely rural area. No two campuses have the same Carnegie classification and the size of the student bodies (head count) ranges from a low of 5190 (CNU) to a high of 10200 (UMBC). CNU has a minimal graduate mission, Oswego offers only Master's degrees, and UMBC grants a substantial number of Ph. D.s each year. Table 1 summarizes this information.

The general student population of each campus also differs. CNU has very few transfer students while Oswego and UMBC attract large numbers of such students.

Oswego has the smallest percentage of full-time students of the three, with 63% of its students so classified. The percentage at UMBC is 74% and at CNU it is 69%. Other characteristics of the sample of students used in this analysis are shown on Tabes 5 through 7 below.

Tables 2 through 4 provide summary information about the courses and the means of delivering the online instruction. For example, Table 2 indicates that each course used a different textbook and two of the three are macro classes and one a micro course. In addition, two courses made use of asynchronous discussion but the third did not, though that course, unlike the other two, used synchronous online discussions. Two of the three courses used WebCT as the course delivery software. The third used TopClass. Grade determination differs across the courses also, as indicated in Table 3. The courses do not all provide the same set of evaluation instruments. For example, not all have graded homework assignments, some assign papers or group projects, and so on. Moreover, even when the two courses use the same instrument, say quizzes, those instruments do not carry the same weight in determining the course grade and they may be administered quite differently.[4]

Many people raise concerns about the administration of exams in web courses.[5] Skeptics of online instruction are concerned about both the security and the validity of the examinations. The courses evaluated here all administered midterm and final

[4]For example, the quizzes given by at one institution allow students five attempts with only the highest score on the quiz counting toward their semester grade. The effects of this approach to quizzes have been studied in Coates and Humphreys (2001a).

[5]One response is to not give exams as a means of evaluation in such courses. Papers and other written assignments, participation in bulletin board discussions, and group or individual projects often form the core of the evaluation in online courses.

examinations, but the precise means of giving them differ somewhat. Table 4 describes these differences. For the online section at UMBC, the instructor emailed the exam to the students, and the students were required to email or fax the completed exam back within three hours. Exams at Oswego are posted on Friday nights and must be returned by Sunday night. The exams are open book, but students are not allowed to work together on them. Students have failed the distance sections of the course for violating this restriction. At CNU, exams are given using the quizzing feature in WebCT. This allows the instructor to set a time limit on the exam, restricting to some extent the student's ability to look for answers in the text. Tests given this way are predominantly multiple choice.[6]

Summary Statistics

Full Sample Summary Statistics

Table 5 presents definitions of the variables and summary statistics on the full sample of students (126 individuals) for whom both SAT and pre- and post-TUCE scores are available. Looking at the full sample, 47% of the students are enrolled in an online class. We also see that 61% of the students work (77 of the 126), and of those that work the average hours per week is 26.2. Average credit hours attempted by students in the sample is about 12.5. About 21% of the students in the sample are transfers, 44% receive financial aid, and 6% are intercollegiate athletes.[7] Thirteen percent of the students

[6] The final exam for the principles course at CNU was given entirely in a multiple choice format to facilitate administration of the post-TUCE. Ordinarily, exams in the course are essay exams.

[7] This definition includes cheerleaders.

belong to fraternities or sororities. In addition, about 37% of the students live on campus. Of those who do not live on campus (81 of the 126), the average commute time is about 18.8 minutes. Twenty-two percent of the students in the sample are freshmen and another 34 percent are sophomores.

The average GPA in the full sample is about 2.8 and the average SAT score is 1098. Interestingly, about 62% of the students consider themselves to be good at math. The survey also asked the respondents to indicate what general area their major is in. Of those responding, 34% said science, math, engineering or computers, 45% said business, and 2% said economics. The remaining students indicated a humanities or social science major. The students were also asked about second majors. The majority, 63%, reported having only one major. However, 37% indicated they had a second major, divided into disciplines as follows: 13% business, 10% science and 3.9% economics, with the rest being humanities or other social science majors.

Looking at the demographic information, 79% of the students in the sample are traditional college age - 17 to 22 years old. Almost 8 percent of them are at least 30 years old. The students in the sample are predominantly white, 68%, but blacks make up about 13% and Asians about 9% of the sample. The students generally have relatively well-educated parents with 45% of fathers and 33% of mothers having earned at least a bachelors degree. However, 44% of fathers and 45% of mothers have no more than a high school education.

We also asked the students about their prior internet experience. The vast majority of students in the full sample have relatively easy access to the internet. Almost 89% of them can access the internet from their home or their dormitory room and 52%

indicated that they had substantial prior experience with the world wide web. This experience did not generally come from usage in courses, however. For example, 69% said that in the course in which they were required to use the internet the most, less than 20% of the course involved use of the internet. Only 7% indicated that their course with the most internet usage involved more than 80% of the course being on the web. Only 43% of those sampled knew anyone who had taken a course entirely via the internet.

We administered the TUCE III at the start of the semester. Students in macro principles took the macro version of the TUCE III, students in micro principles took the micro version. Students at UMBC took both the micro and the macro versions of the TUCE. The average score on each exam is about 10 correct answers, with highs of 19 on the micro test and 20 on the macro test. Low scores in the sample are 3 and 5 on the micro and macro tests, respectively.

Summary Statistics by Campus

Table 6 presents the descriptive statistics by campus. This data does suggest some differences in the students across campuses.[8] For example, almost 71% of students at CNU work while at UMBC and Oswego the figures are 56% and 53%, respectively. Interestingly, working students at CNU work on average of almost six hours more each week than do students at UMBC and about 3.5 hours more than students at Oswego.

Parents of students at the various institutions have rather different educational backgrounds. About 51% of fathers of UMBC students and 53% of fathers of Oswego

[8] Most of the differences in the means between pairs of campuses are statistically significant.

students have at least a bachelors degree, but only 35% of CNU students' fathers do. About 35% of the mothers of UMBC students have bachelors degrees and 46% of Oswego students' mothers do. However, only about 23% of mothers of students at CNU have such degrees.

Based on our sample, UMBC is the most racially diverse of the three campuses. Whereas 49% of UMBC students are white, for CNU and Oswego the numbers are 73% and 88%, respectively. Interestingly, UMBC and CNU have about equal proportions of black students, about 16% at UMBC and 18% at CNU, but at Oswego blacks make up only about 3% of the students in these courses. The greatest disparity in racial composition comes from Asian students, where they comprise 20% of the students at UMBC, 4% at CNU and 0% at Oswego.

Students at UMBC are more likely to be traditional college age than at either CNU or Oswego. The percentages are 89% at UMBC, 71% at CNU and 75% at Oswego. Considering the proportion of students who are 30 years old or older, these individuals are 9% of the total at Oswego, at CNU they are 10% and at UMBC they are just 4%. In addition, Oswego students are more likely to be transfers, 28%, than are CNU or UMBC students where the percentages are 22% and 16%, respectively. The proportion of students receiving financial aid is smaller at Oswego than at either of the other institutions. The figures are 34% for Oswego, 47% for CNU, and 49% for UMBC.

In the courses at UMBC, freshmen are only a small percentage (7%) of the students. At CNU and Oswego, however, freshmen are 22% and 44% of the enrollees in the courses being studied. Interestingly, underclassmen (freshmen or sophomores) in these classes are 53% at UMBC, 65% at CNU, and 47% at Oswego. Students at UMBC reported more experience with the internet, on average, than students at either CNU or Oswego. The percentage reporting the highest level of experience at each institution is 67% at UMBC, 43% at CNU, and 47% at Oswego. High levels of easy access to the web are reported by students at all three campuses with the percentages ranging from 93% at UMBC to 88% at Oswego and 86% at CNU.

Familiarity with the internet in instruction is interestingly distributed. No student at UMBC reported having a course involve more than 80% of the material online. At Oswego the percentage was 9% and at CNU it was 12%.

Students at Oswego are more likely to report living on campus. At Oswego, 47% live on campus, while at UMBC and CNU the percentages are 36% and 31%, respectively. The length of the commute varies considerably among the three campuses. At UMBC the average commute is slightly over 20 minutes, while it is almost 19 minutes at CNU but is under 16.5 minutes at Oswego. The longer commute for UMBC students may reflect the geography of the region around UMBC. Situated southwest of Baltimore at the junction of the Baltimore beltway and Interstate 95, the campus affords easy access to students both from Baltimore and from Washington, DC, and especially the Maryland suburbs of Washington.

Online versus Face to Face Summary Statistics

The focus of this research is on differences in online versus face to face education. A natural first question to ask is whether students in the online sections differ systematically from those in the face to face sections. Table 7 splits the sample by online versus face to face classes.[9] Some differences are immediately clear, and when differences are statistically significant the variable name in the table is followed by *'s. Only about half the face to face students have jobs but 73% of the online students do. In addition, for those that work, hours per week is larger for online students by almost 15, 17.7 versus 32.8. That is, online students work an average of 85% more than do face to face students. Interestingly, face to face students who live off campus have slightly longer commutes, about 2 minutes, than do online students who live off campus. This is probably the result of few of the courses being marketed specifically as a distance education course as compared to simply another section of the regular offerings.[10]

Another strong finding is that face to face students are far more likely to be traditional college age students than are online students, 63% to 93%. The proportion of older students in the online classes is about 10 times that of older students in the face to face classes, 15.3% to 1.5%. Both the proportion of freshmen and underclassmen are larger for the face to face classes than for the online classes. Freshmen are about 36% of face to face students but only about 7% of online students; underclassmen are 73% of face to face students but they are 37% of the students in the web course. Both economics majors and business majors make up slightly larger proportions of the face to face classes than they are of the online classes. However, science majors are a slightly larger share of the online students than they are of the face to face students.

[9]Descriptive statistics from the split between online and face to face by campus are available upon request.

[10]Since commute time is a key variable for us in terms of identifying self-selection effects this finding of no significant difference between commute times for online and face to face students suggests problems with identification.

Transfer students, and members of fraternities and sororities are each larger shares of the online students than of the face to face students. For example, in the online class transfers are 34% of the students, but they are only 10% of the face to face students; fraternity members are 17% of the online class but only 9% of the face to face students. Those individuals receiving financial aid are a smaller proportion of the online class than of the face to face class. Only about 31% of online students receive financial assistance while 57% of face to face students get aid.

One would hypothesize that students in the online classes would have easier access to the internet, more experience with the internet, and have had courses with larger internet content on average than students in the face to face classes. This is largely borne out in the survey responses. Ninety-five percent of online students have easy access to the web, but only 84% of face to face students do. While about equal proportions of students in either type class have had courses using the web for less than 20% of the course, the proportion of online students who have had a course with 80% or more of the course online is 2.5 times that proportion of the face to face students. In addition, 49% of online students report knowing someone who took an online class before signing up for this course whereas only 37% of face to face students say the same thing.

Finally, when the scores on the pretests are compared, the mean scores in the face to face class are 9.92 on the micro TUCE, and 9.73 on the macro TUCE. In the online class the means are, respectively, 9.86 and 9.79. A test of the differences in the means for the pretest scores cannot reject the null hypothesis of no difference.

Empirical Analysis

Model

The basic model used in this analysis is a simple educational production function in which student learning is assumed to be determined by the quantity and the quality of the inputs used in the educational process. These inputs are provided by the student, the instructor, and the educational institution. Student inputs include their initial stock of human capital, their study skills, and the quantity and quality of the time they spend working on the course materials.   Instructor inputs include the quantity and quality of instructional materials, assignments, and feedback. The institution provides the infrastructure for course delivery (including the course management software and servers for online courses).

For the purpose of our model, the measure of educational outcome is the student's post-TUCE score. Three alternative econometric models are used to examine the differential impact of distance learning course delivery on educational outcome:

1. an OLS regression specification,
2. a 2SLS specification, and
3. a switching equations model with endogenous switching.

Basic Statistical Analysis: OLS regression

The basic econometric model is:

$$\text{Post-TUCE}_i = X_i\beta + C_i\delta + \gamma DIS_i + \varepsilon_i \quad (1)$$

where:

X_i = vector of ability and demographic characteristics for student i

DIS_i = 1 if student i is enrolled in a distance learning class (= 0 otherwise)

C_i = vector of instructor-specific dummy variables

$,_i$ = random error term

Under this specification, X_i contains a set of demographic and ability variables that serve as proxies for differences in individual ability, prior schooling, study skills, and the initial stock of subject matter knowledge (as measured by the TUCE exam administered at the start of the term). Differences in instructor quality, instructional styles, course structures, textbooks, and institutional characteristics are captured by the inclusion of instructor-specific dummy variables (C_i) in the regression equation. Note that since each institution has only one instructor this also captures unmeasured institution-specific factors. Under this specification, (is a shift parameter that captures the differential effect of distance learning courses on educational outcomes, holding constant other observable individual characteristics.

A *t*-test on the coefficient (provides a simple test of the relative impact of distance learning course delivery on educational outcomes (as measured by performance on the TUCE exam). The inclusion of interaction terms between the distance learning dummy variable and other individual characteristics makes it possible to examine whether distance learning classes provide larger or smaller benefits for individuals with specific ability and/or demographic characteristics.

A 2SLS Correction

A potential shortcoming of the OLS regression procedure described above is that it is possible that an individual's choice between distance learning and face to face instruction is affected by unobservable differences in ability and learning styles.[11] In this case, OLS estimates of the parameters of equation (1) would be biased and inconsistent due to the endogeneity of the dummy variable $DIS_{i.}$[12] A straightforward 2SLS procedure for this type of endogenous dummy variable problem has been developed by Barnow, Cain, and Goldberger (1981).

To implement this procedure, a selection rule is specified of the form:

$$Z_i = W_i B + u_i \qquad (2)$$

where: Z_i = net benefit (or loss) received by person *i* by selecting a distance learning instead of a face to face course

W_i = vector of characteristics for person *i* that affect the costs and/or benefits associated with the choice of a distance learning course instead of a face to face course.

u_i - N(0,1) = random error term for person *i*[13]

It is assumed that this individual will select a distance learning class if $Z_i > 0$ and a traditional course if $Z_i < 0$. The parameters of equation (2) can be estimated using a probit estimation technique to form:

$$\hat{Z}_i = W_i \hat{B} \qquad (2')$$

Thus, the predicted probability that individual *i* will select a distance learning course is given by:

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[11]The importance of a match between teaching and learning styles in introductory economics classes has been examined in Borg and Shapiro (1996)

[12]An example may help to illustrate why such a bias may occur. Suppose that better motivated students are more likely to enroll in distance learning classes. If these students would have performed better in either type of class, but are over-represented in distance learning classes, the estimated coefficient on the distance learning variable would be biased upward.

[13]Since the variance of the error term in the probit equation cannot be identified, the standard convention of normalizing it to 1 is followed.

$$\widehat{Prob}(DIS_i) = \Phi(W_i\hat{\beta}) \qquad (3)$$

where $\Phi(\cdot)$ is the cumulative density function for the standard normal distribution.

Consistent estimates of the parameters of equation (1) can be derived by using the estimated probabilities from equation (3) as instruments for the endogenous dummy variable DIS_i in a 2SLS estimation procedure.

Identification Issues

To identify the 2SLS model, there must be some variables included in W_i that are not included in X_i.[14] This requires that there be at least one variable that affects the probability of selecting a distance learning course but does not affect the student's educational performance. Since the probit function is essentially a net benefit equation, any factor that affects either costs or benefits belongs in this equation. All of the variables that affect educational performance, however, can not serve to identify the model since they would be expected to affect both educational outcomes and the net

[14]If W_i and X_i are identical, the 2SLS model described above could be identified using the nonlinearity of the probit function in equation (3). This approach, however, would be somewhat troubling since the predicted value of DIS_i would be a nonlinear transformation of the variables contained in X_i. In this situation, it is quite possible that the estimated parameter on the distance learning variable would be primarily capturing nonlinear effects of the variables included in X_i.

A second problem with this identification strategy occurs if there is limited variation in the value of Z_i. in the observed sample. In this case, the instrumental variable estimator would include a generated regressor in the second stage that is approximately a linear function of the X_i. Thus, a multicollinearity problem may appear when W_i and X_i are identical.

benefit associated with the choice. Variables that affect the relative costs of each course delivery mechanism, however, would not be expected to affect course performance. The identification strategy is to assume that commuting time to campus, knowing someone who took an online class, and use of web-based supplemental material in prior face to face classes affect the probability of choosing a distance learning course but do not affect the educational outcome in either type of course.

Switching Equations Model with Endogenous Switching

While the 2SLS procedure discussed above provides a consistent estimator of the effect of the distance learning class on educational outcomes for a typical student, it does not provide any direct information on the impact of self-selection on educational outcomes. Consider, for example, two alternative scenarios:

Scenario I: Individuals who select distance learning courses are more able and would have performed better in either type of course. Individuals who select face to face courses are less able and would perform less well in either type of course. (An equivalent situation would occur if students in face to face courses would have performed better in either type of course.)

Scenario II: Individuals with learning styles that are compatible with distance learning courses have an above average performance in distance learning courses, while individuals who select face to face courses have above average performance given this choice.

To distinguish between these two scenarios (and other possibilities), it is necessary to determine whether the selectivity bias is, on average, negative or positive in the observed samples. This cannot be directly determined from either the OLS or the

2SLS estimation procedures described above. To investigate this issue, a switching equations model with endogenous switching is specified.[15]

The basic model that we investigate is given by:

$$\text{Post-TUCE}_i^D = X_i\beta^D + C_i\delta^D + \varepsilon_i \tag{4}$$

$$\text{Post-TUCE}_i^F = X_i\beta^F + C_i\delta^F + \eta_i \tag{5}$$

$$Z_i = W_i\gamma + u_i \tag{6}$$

where:

a D superscript indicates individual *i* selected a distance learning course

an F superscript indicates an individual *i* selected a face to face course

X_i = vector of individual ability and demographic characteristics for person *i*

C_i = vector of instructor-specific dummy variables

W_i = vector of characteristics for person *i* that affect the costs and/or benefits associated with the choice of a distance learning course instead of a face to face course.

$[\varepsilon_i \;\; \eta_i \;\; u_i]' \sim N(\mathbf{0}, \boldsymbol{\Sigma})$

Equations (4) and (5) indicate that the Post-TUCE score received in either a distance learning course or a face to face course is a function of the individual's ability and demographic characteristics and the instructor and institutional characteristics that are captured by the instructor dummy variables. Notice that this specification allows the institutional and instructor effects to be different in the online and face to face equations.

[15] Willis and Rosen (1979) have used a model of this sort to examine the return to education. A good discussion of this model appears in Maddala (1983), pp. 283-7.

Equation (6) is a net benefit equation that is a measure of the net benefit received by selecting a distance learning course instead of a face to face course.[16]

The selection rule, as in the previous model, indicates that an individual is assumed to select a distance learning class if Z_i is positive and a face to face class if Z_i is negative. Under the assumptions of the model above:

$$E\,[\,\text{Post-TUCE}_i^D \mid \text{DIS}_i = 1] = X_i\$^D + C_i{*}^D + F_{,u}\, 8_i^D \qquad (7)$$

$$E\,[\,\text{Post-TUCE}_i^F \mid \text{DIS}_i = 0] = X_i\$^F + C_i{*}^F + F_{0u}\, 8_i^F \qquad (8)$$

where: $F_{,u} = \mathrm{cov}(\,,_i, u_i)$

$F_{0u} = \mathrm{cov}(0_i, u_i)$

$$8_i^D = \frac{N(W_iB)}{M(W_iB)}$$

$$8_i^F = \frac{-\,N(W_iB)}{1 - M(W_iB)}$$

$N(\cdot)$ is the probability density function for a N(0,1) variable

$M(\cdot)$ is the cumulative density function for a N(0,1) variable

Consistent estimates of all model parameters may be constructed by the two-stage estimation process developed by Heckman (1976, 1979). In the first stage, the parameters of the reduced-form probit equation (equation 6) are estimated using a maximum

[16] A more elaborate specification could include a structural probit model in which the probability of selecting a distance learning class is a function of (Post-TUCE$_i^D$ - Post-TUCE$_i^F$).

likelihood estimation technique. Estimated values of $W_i\hat{B}$ are used to form estimates of $\hat{\lambda}_i^D$ and $\hat{\lambda}_i^F$ which are the conditional expectation of u_i given one is in the online and face to face courses, respectively. Consistent estimates of the remaining model parameters may be found by estimating the following equations by OLS:[17]

$$\text{Post-TUCE}_i^D = X_i\beta^D + C_i\delta^D + \gamma^D\hat{\lambda}_i^D + \varepsilon_i \quad (9)$$

$$\text{Post-TUCE}_i^F = X_i\beta^F + C_i\delta^F + \gamma^F\hat{\lambda}_i^F + \eta_i \quad (10)$$

The estimation of the equations above may be used to generate an estimate of the change in TUCE score that a student may receive by selecting a distance learning rather than a conventional mode of instruction.[18]

For an individual randomly selected from the population, the predicted difference in this individual's TUCE score from being in a distance learning class instead of a face to face class is given by:

$$\widehat{\Delta \text{TUCE}}_i = X_i(\hat{\beta}^D - \hat{\beta}^F) + C_i(\hat{\delta}^D - \hat{\delta}^F)$$

Model Comparison

[17]While OLS provides consistent estimates of all parameter estimates, the OLS standard errors are biased. Consistent estimates of the standard errors are derived using the procedure described by Greene (1979). The identification issues in this model are similar to those described in the 2SLS model above. As in the previous model, identification is achieved by including commuting time as variable in W_i that does not appear in X_i.

[18]The estimated change in TUCE scores may be measured as either an unconditional or a conditional change. An unconditional change is one that is based only on observable characteristics. The conditional change in the TUCE score would also take into account the expected value of the error term for an individual with a given set of characteristics. A good discussion of the distinction between conditional and unconditional changes in models of this sort may be found in Gyourko and Tracy (1988). For reasons that will be discussed below, we present only the unconditional change in TUCE scores.

A more intuitive comparison of the three models described above may be useful. The OLS specification is appropriate only if:

- the decision to select the mode of instruction is unrelated to each student's expected performance under each method of instruction, and
- the selection of a distance learning course will cause each student's final TUCE score to differ by a constant amount (() from the TUCE score they would have received in a face to face course. In particular, this means that all measured ability, family background, and demographic characteristics have identical effects on performance under both modes of instruction.

The 2SLS model is an appropriate specification if the first, but not the second, of these conditions is violated. When both of these conditions are violated, the switching equations model is appropriate.

Results and Discussion

Table 8 shows results of OLS estimation of Equation (1). The results on Table 8 reflect two different specifications for the vector of ability and demographic characteristics, X_i, for each student. In each case, the student's score on the TUCE administered at the end of the semester is the dependent variable. The model TUCE2 includes both a dummy variable that equals one if the student has a job and the log of the hours the student worked at this job each week as explanatory variables. The model TUCE1 excludes these explanatory variables. We estimated these alternative specifications because there is some disagreement in the literature about the importance of variables reflecting time spent on course work. Siegfried and Walstad (1998) report only one study, by Paul (1982), that finds that outside employment influences academic performance but three that find that time spent studying has a negative or an insignificant effect on achievement.[19]

In these results, the variable *online,* which equals one if the student was enrolled in an online section of principles, has a negative coefficient (1.67 to 1.78) which is significant at the 10% level or better. These point estimates suggest that students in the online sections correctly answered about two fewer questions on the TUCE than students in the face to face sections. Freshmen and sophomores scored slightly lower than juniors and seniors, students on financial aid scored slightly lower than those students who were not on financial aid, and in both sections each additional 100 points on the SAT was associated with slightly less than one additional correctly answered question. The pre-test score on the TUCE is statistically significant in either specification and implies that four additional correct answers on the pre-test translate into one additional correct answer on the post-test.

Recall that one possible problem with these OLS estimates is that they could suffer from sample selection bias; the estimated impact of the treatment variable, *online* in this case, could be biased because students could select themselves into either section depending on unmeasured preferences or ability. We employed a two-stage least squares (2SLS) procedure to correct for the effects of sample selection bias. The results of this correction are shown on Table 9.

The first set of results, in columns two and three of Table 9, are from the first stage, or selection model, correction for selection bias. The first stage uses a probit

[19]The three studies are: Gleason and Walstad (1988), Grimes, et al. (1989), and Durden and Ellis (1995).

estimator to estimate the probability that a given student enrolled in an on-line section. In order to identify the selection model, some variables must be included in the selection model that do not appear in the second-stage regression. Ideally, these variables should be correlated with the student's enrollment choice but not with the student's academic performance. Like the OLS regressions, we use two sets of identifying variables, reflected in the columns labeled TUCE1 and TUCE2. Both sets contain the student's commute time to campus, a dummy variable for students living on campus, a dummy variable indicating those students who had a friend who had previously taken an on-line class, and a dummy variable indicating those students in the top quintile of the sample in terms of previous use of the internet in classes. TUCE1 also included the job dummy variable and the log of hours worked as identifying variables in the selection model.

The estimates of the selection model show that working and having a friend who previously took an online course both had a significant impact on the likelihood that a student enrolled in an online sections. Transfer students are more likely, and freshmen and sophomores, and students on financial aid significantly less likely to enroll in an on-line section.

The 2SLS correction uses the fitted values from the first-stage regression, the estimated probability that a student would have enrolled in an on-line section, instead of the dummy variable indicating those students who actually enrolled in the on-line sections, as an explanatory variable in the second stage regression. This variable is *probonline* on Table 9. The standard errors reported on Table 9 have been corrected to account for the two-stage estimation procedure. Again, the variables reflecting non-academic work may or may not belong in the second stage regression - an education production function - so we have estimated the model with (TUCE2) and without (TUCE1) these variables in the second stage regression.

The results shown in columns four through seven on Table 9 indicate that our results are robust to the specification of the model in terms of the non-academic work variables. The results for TUCE1 and TUCE2 are quite similar. Foremost among the results on this table are those capturing the effect of enrollment in the on-line sections, *probonline*, on student's performance on the TUCE. For both specifications, the parameters on this variable are negative. In the TUCE1 model the parameter estimate is statistically significantly different from zero at the 10% level.[20] After correcting for sample selection bias, students in the on-line sections correctly answered between four and six fewer questions on the TUCE than students in the face to face sections. Since there are only 33 questions on the TUCE exam, this range of additional incorrect answers accounts for 12 to 18% of the total. In other words, this evidence indicates that students in online principles-level courses miss between 12 and 18% of the total questions more than otherwise identical students from face to face classes. This suggests fairly large costs in terms of reduced learning of delivering principles of economics instruction entirely via the internet.

The other significant variables in the second stage regressions are correctly signed. Students who scored higher on the TUCE administered at the beginning of the semester tended to score higher on the TUCE administered at the end of the semester, each additional 100 points on the SAT was associated with correctly answering about one

[20]While the coefficient estimate is not statistically significant at the 10% level in the TUCE2 model, the p-value is 0.102 so it is very close to significant at that level.

additional question on the TUCE and students receiving financial aid tended to answer fewer questions correctly.

Note that freshmen and sophomores also tended to answer fewer questions correctly than juniors and seniors. This, coupled with the negative sign on the on-line variable, again suggests that teaching principles-level economics courses over the WWW is a bad idea. The freshmen and sophomores enrolled in these sections would be expected to correctly answer between six and eight fewer questions correctly on the TUCE than juniors or seniors in face to face sections.

Table 10 reports the results of estimating the endogenous switching model. Specifically, using coefficient estimates from the probit equation reported in Table 9, 8^{D} and 8^{F} are computed for each observation. After splitting the sample between the online and face to face classes, 8^{D} is added to the online section's equation and 8^{F} is added to the face to face section's equation. In Table 10, this additional variable is referred to as lambda. As before, the model is estimated both with and without the job and log of hours worked variables.

Note that the variables in the model do very little individually to explain the outcome on the TUCE for the face to face students. The exceptions to this are the ease of access to the web, score on the TUCE before taking the course, whether the student receives financial aid, and the student's performance on the SAT. Most importantly, the lambda variable is not statistically significant whether the job variables are included or not. This means that there is no significant self-selection bias in the face to face equations.[21] Students who select face to face classes have a level of performance that is not significantly different from that of a random student in the population that has the same set of observable characteristics.

Turning to the online students, the results reveal a somewhat different picture. Several of the variables are statistically significant, with underclassmen and those receiving financial aid scoring significantly lower than upperclassmen and those not receiving aid, and transfer students and those who consider themselves good at math doing better than other students.

But the most interesting result in the online equations is the estimated coefficient for the self-selection variable in the online equation. This estimated parameter has a positive sign and estimated coefficients of 3.18 and 4.79 with p-values of .051 and 0.13, respectively, under the two specifications of this equation. The implication of this result is that those students who selected the online class performed better in this type of class than would an otherwise identical student who had instead chosen a face to face class. In particular, as compared to a random person in the population with identical characteristics, those who voluntarily selected a distance learning course received an estimated increase in their TUCE score of 2.30 under equation specification TUCE2 (or 1.52 under specification TUCE1).[22] To see this, consider equation (7). The positive

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[21]The positive coefficient on the $\hat{8}$ term in the face to face equations, though, would suggest that individuals in face to face classes perform less well in this type of class than would a random person selected from the entire population. This result, combined with the positive selectivity bias found in the distance learning equation, suggests that students in distance learning courses, on average, have higher levels of unobservable ability that improves their performance under both types of instruction.

[22]The estimated change in TUCE score resulting from the self-selection process can be computed as the product of the estimated coefficient on the lambda value and the mean value of lambda in the subsample of students in a distance learning class.

estimated value of 8 for the online class suggests that those factors that are unobserved but induce one to take an online class are correlated with those unobserved factors that enable one to do well in such a class.

As noted above, the endogenous switching equations model allows us to generate an estimate of the change in the TUCE score that results from selecting an online course. The estimated change in TUCE scores, evaluated at the overall mean for the entire sample equals -6.35 under the TUCE1 specification and -5.75 under the TUCE2 specification. This suggests that a "typical" person would receive approximately 6 fewer correct responses (out of 33) on the TUCE exam by choosing an online course rather than a face to face course. This result is very similar to that found under the 2SLS specification presented above. It offers further evidence suggesting that the distance learning delivery option adversely affects student performance when the self-selection process is taken into account.

Since three of the four estimated parameters on the selectivity bias equation are insignificant at a 10% significance level, we cannot draw very strong conclusions about the extent to which the return to a distance learning course differs across individuals. The results suggest, however, that those who select distance learning classes, on average, suffer a smaller decline in their performance than would a typical person in the population.

We do not have information on whether the students in the online sections found the experience enjoyable, or whether they are more or less likely to take additional economics classes. A large literature exists in which such evidence is found and reported as support for further online education. Our results are consistent with the results found in this literature. Feeling happy about the experience of an online class that one choose to take may be the result of doing better in that class than one expected to do in the face to face version.

Conclusion

Our analysis reveals that self-selection into online classes is an important issue in the assessment of the effectiveness of online education in economics. Failure to account for the effects of selection leads to biased and inconsistent coefficient estimates in education production functions and may result in misleading inferences regarding "no significant difference" between online and face to face instruction. Indeed, under the 2SLS specification, we find that failure to account for the selection issue biases toward zero the differential between scores on the TUCE from students taking principles of economics face to face and those taking it online. The differential is a statistically significant 3 to 6 fewer correct answers by online students compared to face to face students. Moreover, an endogenous switching equations model provides further support for this result. This model also suggests that those who select a distance learning course perform better than would a randomly selected individual with identical observable characteristics. There is also some evidence that underclassmen, freshmen and sophomores, are also especially vulnerable to underperforming in online classes relative to how they would fare in a face to face class. This is an especially troubling result given the findings of Coates and Humphreys (2001a) that the number of online principles of economics courses is on the rise, and the suggestion that online instruction may be a viable means of addressing the lack of physical plant needed to meet the demands of growing numbers of undergraduates (Navarro 2000).

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Table 1: Institutional Characteristics				
Institution	Carnegie classification	Undergraduate (Graduate) Enrollment	Location	Students
Christopher Newport University	Baccalaureate - Liberal Arts	5000 (190)	Urban or suburban	69% full-time 10% transfers
State University of New York College at Oswego	Master's (Comprehensive) Colleges and Universities I	7000 (1000)	Rural	63% full-time 36% transfers
University of Maryland, Baltimore County	Doctoral/Research University - Extensive	8800 (1400)	Urban or suburban	74% full-time 31% transfers

Table 2: Course, Textbook, and Web Delivery Characteristics					
Institution	Course	Text	Online Delivery and Management	Asynchronous Online Discussion	Synchronous Online Discussion
CNU	Macro	Miller	WebCT	Yes	No
Oswego	Micro	Boyes/Melvin	TopClass	Yes	No
UMBC	Macro	Mankiw	WebCT	No	Yes

Table 4: Administering Online Exams	
UT- Dallas	Students take exams in a monitored room set aside for this purpose.
CNU	Administered online.
Oswego	Administered online.
UMBC	Distributed via email, returned via email or fax. Short answer and problem type questions.

Table 3: Assignments and Grade Determination			
	CNU	Oswego	UMBC
Homeworks or Problem Sets	No	Graded	Ungraded
Online Quizzes	Yes (participation credit)	Yes	Yes
Group Assignments or Projects	Yes (online only)	No	No
Participation	No	Yes	No
Written Assignments	Yes (face to face only)	No	No
Midterm Exam or exams	Yes	Yes	Yes
Final Exam	Yes	Yes	Yes
Extra Credit[a]	Yes	Yes	Yes

[a]Each of us gave extra credit to the students for completing a survey used to gather socio-demographic variables needed for the empirical analysis.

Table 5: Full sample descriptive statistics and variable definitions

Variable	Definitions	Mean	Std. Dev.	Min	Max
transfer	1 if the student is a transfer student	0.214	0.412	0	1
satnew	Total score on the SAT	1097.675	152.736	650	1530
job	1 if student had a job	0.611	0.489	0	1
jobhrs	Hours worked if job=1	26.175	14.933	0	60
oncampus	1 if student lives on campus	0.365	0.483	0	1
commute	minutes to campus from home	18.827	14.379	0	65
finaid	1 if the student receives financial aid	0.444	0.499	0	1
frat	1 if the student is a member of a fraternity or sorority	0.127	0.334	0	1
athlete	1 if the student is a student athlete	0.063	0.245	0	1
goodmath	1 if the student considers himself or herself good at math	0.619	0.488	0	1
gender	1 if the student is male	0.516	0.502	0	1

fatherba	1 if father has a bachelors degree or more	0.452	0.500	0	1
motherba	1 if mother has a bachelors degree or more	0.333	0.473	0	1
white	1 if the student is caucasian	0.683	0.467	0	1
black	1 if the student is black	0.135	0.343	0	1
asian	1 if the student is asian	0.087	0.283	0	1
science	1 if the student is a science or math major	0.341	0.476	0	1
business	1 if the student is a business major	0.452	0.500	0	1
economic	1 if the student is an economics major	0.024	0.153	0	1
undercl	1 if the student is a freshman or sophomore	0.563	0.498	0	1
easeacc	1 if the student's web access is at home or in his dormitory	0.889	0.316	0	1
exper	1 if the student has a great deal of experience with the internet	0.524	0.501	0	1
topquint	1 if the course with most web content had more than 80% on the web	0.071	0.259	0	1
friend	1 if the student knew someone who had a web course	0.429	0.497	0	1
tradage	1 if the student is between 17 and 22	0.786	0.412	0	1
older	1 if the student is 30 or older	0.079	0.271	0	1
online	1 if in the web class	0.468	0.501	0	1
post_t	student's score on end of term TUCE	12.754	4.550	4	26
pre_t1	student's score on start of term TUCE	9.794	3.183	5	20
umbc	1 if student attends UMBC	0.357	0.481	0	1
cnu	1 if student attends Christopher Newport Univ.	0.389	0.489	0	1
oswego	1 if student attends Oswego State	0.254	0.437	0	1
N		126			

Table 6: Descriptive Statistics by Institution

	UMBC		CNU		Oswego	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
transfer	0.156	0.367	0.224	0.422	0.281	0.457
satnew	1162.222	120.753	1030.408	150.107	1109.906	158.512
job	0.556	0.503	0.714	0.456	0.531	0.507
jobhrs	23.060	12.589	28.914	12.978	25.118	20.757
oncampus	0.356	0.484	0.306	0.466	0.469	0.507
commute	20.241	14.574	18.857	14.496	16.353	14.335
finaid	0.489	0.506	0.469	0.504	0.344	0.483
frat	0.156	0.367	0.184	0.391	0.000	0.000
athlete	0.089	0.288	0.041	0.200	0.063	0.246
goodmath	0.644	0.484	0.592	0.497	0.625	0.492
gender	0.467	0.505	0.592	0.497	0.469	0.507
fatherba	0.511	0.506	0.347	0.481	0.531	0.507
motherba	0.356	0.484	0.224	0.422	0.469	0.507
white	0.489	0.506	0.735	0.446	0.875	0.336
black	0.156	0.367	0.184	0.391	0.031	0.177
asian	0.200	0.405	0.041	0.200	0.000	0.000
science	0.578	0.499	0.224	0.422	0.188	0.397
business	0.289	0.458	0.490	0.505	0.625	0.492
economic	0.067	0.252	0.000	0.000	0.000	0.000
undercl	0.533	0.505	0.653	0.481	0.469	0.507
easeacc	0.933	0.252	0.857	0.354	0.875	0.336
exper	0.667	0.477	0.429	0.500	0.469	0.507
topquint	0.000	0.000	0.122	0.331	0.094	0.296
friend	0.333	0.477	0.612	0.492	0.281	0.457
tradage	0.889	0.318	0.714	0.456	0.750	0.440
older	0.044	0.208	0.102	0.306	0.094	0.296
online	0.489	0.506	0.429	0.500	0.500	0.508
post_t	14.178	4.992	11.653	3.401	12.438	5.022
pre_t1	10.267	3.532	9.286	2.836	9.906	3.156
N	45		49		32	

Table 7: Descriptive Statistics by Instructional Type

	Face to face				Online			
	Mean	**Std. Dev.**	**Min**	**Max**	**Mean**	**Std. Dev.**	**Min**	**Max**
transfer*	0.104	0.308	0	1	0.339	0.477	0	1
satnew	1079.806	141.912	720	1530	1117.966	163.008	650	1500
job*	0.507	0.504	0	1	0.729	0.448	0	1
jobhrs*	17.735	10.555	0	40	32.849	19.261	5	60
oncampus*	0.507	0.504	0	1	0.203	0.406	0	1
commute**	20.091	13.239	0	45	17.958	15.189	0	65
finaid*	0.567	0.499	0	1	0.305	0.464	0	1
frat	0.090	0.288	0	1	0.169	0.378	0	1
athlete	0.075	0.265	0	1	0.051	0.222	0	1
goodmath	0.642	0.483	0	1	0.593	0.495	0	1
gender	0.478	0.503	0	1	0.559	0.501	0	1
fatherba	0.463	0.502	0	1	0.441	0.501	0	1
motherba	0.284	0.454	0	1	0.390	0.492	0	1
white	0.672	0.473	0	1	0.695	0.464	0	1
black	0.119	0.327	0	1	0.153	0.363	0	1
asian	0.104	0.308	0	1	0.068	0.254	0	1
science	0.328	0.473	0	1	0.356	0.483	0	1
business	0.507	0.504	0	1	0.390	0.492	0	1
economic	0.030	0.171	0	1	0.017	0.130	0	1
undercl*	0.731	0.447	0	1	0.373	0.488	0	1
easeacc*	0.836	0.373	0	1	0.949	0.222	0	1
exper	0.478	0.503	0	1	0.576	0.498	0	1
topquint	0.045	0.208	0	1	0.102	0.305	0	1
friend	0.373	0.487	0	1	0.492	0.504	0	1
tradage*	0.925	0.265	0	1	0.627	0.488	0	1
older*	0.015	0.122	0	1	0.153	0.363	0	1
post_t	12.791	4.953	4	26	12.712	4.086	6	25
pre_t1	9.627	3.074	5	18	9.983	3.319	5	20
umbc	0.343	0.478	0	1	0.373	0.488	0	1
cnu	0.418	0.497	0	1	0.356	0.483	0	1
oswego	0.239	0.430	0	1	0.271	0.448	0	1
N	67				59			

*P-value less than 0.05 on test of equality of means between online and face to face

**P-value less than 0.10 on test of equality of means between online and face to face

Table 8: OLS Regression Results

	TUCE 2		TUCE 1	
	Coeff.	**s.e.**	**Coeff.**	**s.e.**
job	-2.846	1.908		
lnjobhr	0.198	0.604		
fatherba	-0.170	0.792	0.107	0.808
motherba	0.338	0.839	0.479	0.861
white	0.638	1.370	0.508	1.384
black	0.153	1.620	-0.484	1.642
asian	0.544	1.751	0.330	1.794
economic	-1.899	2.771	-2.126	2.809
business	0.589	1.036	0.256	1.046
science	0.994	1.202	0.440	1.218
undercl	-1.958	0.831 b	-1.324	0.823
easeacc	1.710	1.283	1.505	1.295
exper	0.607	0.850	0.510	0.863
transfer	0.647	0.976	0.714	1.004
finaid	-2.247	0.818 a	-1.919	0.833 b
athlete	-1.112	1.590	-0.626	1.622
goodmath	1.031	0.812	1.216	0.830
frat	0.275	1.148	0.150	1.181
pre_t1	0.253	0.132 b	0.287	0.135 b
umbc	1.742	1.121	1.847	1.151
cnu	0.912	1.009	0.625	1.003
gender	-0.137	0.814	-0.266	0.825
satnew	0.006	0.003 c	0.006	0.003 c
online	-1.678	0.897 c	-1.775	0.848 b
_cons	3.714	3.453	1.946	3.413
Adjusted R^2	.31		.27	
N	126		126	

[a]: Significant at 1% Level
[b]: Significant at 5% Level
[c]: Significant at 10% Level

Table 9: 2SLS Correction for Selection Bias

Variable	Selection Model Coeff.	s.e.	p-value	TUCE 2 Coeff.	s.e.	p-value	TUCE 1 Coeff.	s.e.	p-value
job	-2.407	0.883	0.01	-5.478	3.018	0.073			
lnjobhr	0.931	0.293	0.00	1.229	1.078	0.257			
fatherba	-0.615	0.361	0.09	-0.658	0.958	0.494	-0.176	0.871	0.840
motherba	0.460	0.364	0.21	0.718	0.969	0.460	0.613	0.885	0.491
white	0.893	0.632	0.16	1.009	1.528	0.511	0.471	1.408	0.739
black	0.814	0.695	0.24	0.431	1.785	0.810	-0.477	1.670	0.776
asian	0.418	0.760	0.58	0.487	1.913	0.800	0.179	1.831	0.922
economic	-1.345	1.627	0.41	-3.048	3.179	0.340	-2.257	2.861	0.432
business	-0.600	0.446	0.18	-0.101	1.270	0.937	0.083	1.079	0.939
science	-0.632	0.520	0.22	0.172	1.483	0.908	0.150	1.274	0.906
undercl	-0.914	0.358	0.01	-2.832	1.159	0.016	-1.740	0.933	0.065
easeacc	0.655	0.620	0.29	2.331	1.494	0.122	1.607	1.322	0.227
exper	0.103	0.379	0.79	0.748	0.936	0.426	0.695	0.897	0.440
transfer	1.099	0.478	0.02	1.760	1.410	0.215	1.200	1.131	0.291
finaid	-0.777	0.354	0.03	-3.176	1.175	0.008	-2.364	0.954	0.015
athlete	0.709	0.762	0.35	-0.628	1.783	0.725	-0.519	1.654	0.754
goodmath	-0.467	0.387	0.23	0.800	0.905	0.379	1.030	0.862	0.235
frat	0.523	0.511	0.31	0.736	1.310	0.576	0.403	1.226	0.743
pre_t1	0.024	0.055	0.66	0.271	0.145	0.065	0.297	0.138	0.034
umbc	0.341	0.501	0.50	2.057	1.253	0.104	1.928	1.174	0.103
cnu	-0.531	0.480	0.27	0.533	1.147	0.643	0.658	1.021	0.521
gender	0.202	0.366	0.58	0.173	0.921	0.852	0.006	0.877	0.995
satnew	0.001	0.002	0.59	0.006	0.004	0.088	0.007	0.004	0.055
probonline				-5.638	3.418	0.102	-3.371	1.810	0.065
oncampus	-0.293	0.455	0.52						
topquint	0.138	0.707	0.85						
friend	0.678	0.367	0.06						
commute	-0.009	0.015	0.54						
constant	-1.560	1.831	0.39	4.797	3.885	0.220	1.886	3.471	0.588
Adjusted R^2									
N	126			126			126		

Table 10: Endogenous Switching Regressions

Variable	Face to face Coeff.	s.e.	Online Coeff.	s.e.	Face to face Coeff.	s.e.	Online Coeff.	s.e.
job	--	--	--	--	-1.807	3.797	-6.033	6.365
lnjobh	--	--	--	--	-0.342	1.425	1.623	2.030
fatherba	-0.892	1.104	-0.313	1.245	-0.994	1.146	-0.343	1.639
motherba	2.033	1.197[c]	-0.715	1.336	1.704	1.183	-0.324	1.862
white	-1.522	1.917	0.435	1.992	-1.016	1.812	1.110	2.818
black	-0.278	2.182	-2.129	2.318	0.838	2.036	-1.760	3.140
asian	-1.705	2.379	-2.885	2.674	-1.317	2.135	-1.765	3.744
economic	-3.799	3.743	-4.015	4.154	-3.437	3.702	-3.607	5.517
business	1.658	1.513	-1.367	1.542	1.678	1.610	-1.424	2.273
science	0.254	1.764	-0.902	1.755	0.963	1.804	-1.196	2.561
undercl	-1.254	1.175	-3.065	1.352[b]	-1.651	1.468	-3.925	1.934[b]
easeacc	3.562	1.638[b]	0.323	2.702	3.524	1.576[b]	1.760	3.994
exper	1.789	1.207	-0.767	1.195	2.034	1.094[c]	-0.640	1.603
transfer	0.196	1.879	2.630	1.282[b]	-1.240	2.399	3.129	1.758[c]
finaid	-2.033	1.195[c]	-3.464	1.410[b]	-2.272	1.324[c]	-3.792	1.894[b]
athlete	1.201	2.102	-1.226	2.374	0.027	2.011	-0.791	3.271
goodmath	-1.056	1.120	2.708	1.205[b]	-0.932	1.038	2.707	1.632[c]
frat	-0.723	2.009	1.644	1.566	-0.714	1.918	1.611	2.057
pre_t1	0.499	0.200[b]	0.140	0.185	0.515	0.181[a]	0.121	0.249
cnu	0.765	1.342	0.692	1.376	0.935	1.374	0.733	1.887
umbc	3.004	1.755[b]	2.218	1.528	2.866	1.664[c]	2.306	2.028
gender	-0.527	1.204	0.939	1.175	-0.327	1.086	0.929	1.595
satnew	0.010	0.006[c]	0.009	0.004[b]	0.006	0.006	0.009	0.005[c]
lambda	2.068	1.811	3.176	1.624[b]	1.013	2.776	4.790	3.184
Constant	-3.933	5.952	-1.195	4.895	0.827	6.138	-2.629	7.116
N	67		59		67		59	
adj. R^2	.31		.34		.35		.34	

[a]: Significant at 1% Level
[b]: Significant at 5% Level
[c]: Significant at 10% Level