Research in Economic Education

In this section, the *Journal of Economic Education* publishes original theoretical and empirical studies of economic education dealing with the analysis and evaluation of teaching methods, learning, attitudes and interests, materials, or processes.

PETER KENNEDY, Section Editor

Teaching and Learning Principles of Microeconomics Online: An Empirical Assessment

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Abstract: How do students enrolled in online courses perform relative to those who choose a more traditional classroom environment? What student characteristics help explain differences in student academic achievement in the two modes of instruction? What factors affect the students' choice of instruction mode? The authors address these questions in relation to the teaching of introductory economics courses. They find that the two groups of students are significantly different in age, gender composition, marital status and number of children, GPA, previous economics exposure, planned major, and other important characteristics. The raw data suggested a higher mean score for the online class sections. But after considering course selection bias, the findings indicated that age and GPA positively affect students' performance in the course, whereas the online teaching mode has a narrowly insignificant, or even negative, effect. Semester effects are most important for the online subsample, and male students enjoy a premium in the traditional classroom setting.

Keywords: academic achievement, online teaching, principles of microeconomics, self-selection
JEL codes: A20, A22

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Online learning has been described as a solution to some of the educational challenges emerging in the twenty-first century. As the children of the baby boomers enter college, both public and private universities face greater student enrollments and reduced budgets. This surge in enrollment figures has created financial strains on many colleges across the nation. At the same time, students reside at greater distances from their universities and face increasing work and family demands on their time (Bonca 1998). Colleges and universities have therefore implemented alternatives to the traditional classroom-based experience, ranging from Web-based delivery of certain classroom materials to complete online instruction.

Does online education represent a cost-effective solution to these challenges while maintaining or improving teaching quality? Might the new technology somehow reduce the long-standing gender gap in economics? We address the literature on these two questions. Next we present our study, which uses a data set that allows for a decomposition of test scores by teaching mode and gender. We specifically investigate the variables affecting course selection and performance for students enrolled in economics principles courses and present results of the empirical analysis.

LITERATURE ON ONLINE EDUCATION

A widespread debate has begun to emerge among academics regarding Internet technology. Sosin (1998) provided an overview of the arguments. On the positive side, an online class provides faster information access, it can be structured to accommodate different learning styles and student types, and it encourages students to take a more responsible, constructive role in the learning process (Zhang 1998; Brewer and Erickson 1997; McCollum 1997). More time is available for studying when long travel times to a distant campus are eliminated, and students enrolled in online classes can gain computer skills useful for future career paths (Agarwal and Day 1998). Student-professor interaction may be enhanced by online instruction. The distance-learning format allows the instructor to rely on asynchronous communication for content delivery, dedicating the time spent (synchronously) online with the students to class discussion and student-instructor interaction (Navarro and Shoemaker 2000a). Finally, if the online classroom is at least as effective a learning environment as the traditional classroom, education delivery costs per student and per concept taught could be lowered, therefore lowering the total costs of education.

Others point to traditional classroom benefits such as immediate response to student questions and frequent student-to-student interaction (Zhang et al. 2004). Furthermore, potential advantages of online learning, such as provision of individualized instruction to accommodate different learning styles and use of interactive, hands-on learning materials, would not be realized if the online instructor structures the Web-based course as a replica of the traditional course. Students may then worry about memorization more than they would in the traditional setting (Twigg 2001). Technical problems related to the Web infrastructure and to system incompatibilities are common, and higher withdrawal rates occur in online teaching (Navarro 2000). Bredon and Shanahan (2000) offered a critical analysis of both costs and product characteristics of online instruction.

A parallel debate exists around gender performance differentials in economics. Siegfried (1979) reviewed the literature on the gender gap in students' performance in standardized, multiple-choice examinations. In most cases, the evidence indicates a statistically significant, although often small, male advantage over females in the understanding of economics concepts. Later works on high school economic literacy by Watts (1987), Walstad and Soper (1989), Evans (1992), and Walstad and Robson (1997) reported statistically significant gender differences favoring males. Qualitatively similar results on the effect of gender on test scores measuring economic knowledge are obtained in studies of economic literacy at the college level. Lopus (1997), for example, determined an average male advantage on the TUCE macro and micro pretest for a national sample of students divided across principles of microeconomics and macroeconomics entry-level college courses, after controlling for students' exposure to economic education in high school and for student abilities as measured by SAT scores.

Changing the teaching format may help to reduce the gender gap in economics. Online teaching could favor female students intimidated in a traditional coed lecture setting. If female students are those more likely to hold many responsibilities (including family, work, and study), online courses could represent a time-saving innovation that would enhance the performance of this subgroup. But there are few rigorous studies to document the process through which students decide between online and traditional teaching formats, particularly with an eye toward gender outcomes, and only a handful of studies have compared the factors linking sorting and student performance in traditional versus online delivery systems.

Some Lessons from Social Science

Online teaching and learning methods have been implemented across nearly all academic disciplines. Some studies have focused on student satisfaction and persistence as indicators of class quality, with these indicators ultimately affecting students' test scores and grade outcomes. For instance, McLaren (2004) found that online classes have higher dropout rates than traditional lecture-based classes; however, those students who did persist in attending the online section received grades similar to their lecture counterparts. McFarland and Hamilton (2005) found no difference in student satisfaction or performance between those enrolled in online and lecture sections. Turning mainly to student exam performance results, Russell (2006) reviewed 355 research studies and found that, in most cases, learning outcomes are comparable across teaching modes.

Regarding economics, in 2000 more than 50 institutions offered at least 100 online economics courses (Navarro 2000), and although many U.S. economists still rely on "chalk-and-talk" lecture delivery with some technology enhancements (Becker and Watts 2001), the number of universities offering online economics courses has grown. The online component varies from the simple use of e-mail after lectures and postings of some course materials and online quizzes to full online content delivery and testing or teleconferencing. Most offerings, and related studies, focus on introductory economics. As Navarro and Shoemaker (2000a) emphasized, this body of literature consists typically of case studies rather than rigorous, controlled comparison of learning outcomes between live, lecture-based economics and economics online. A common trend is to integrate Web-based news or active games (e.g., Iowa Electronic Markets) into class work (Simkins 1999) or to use course Web pages and online quizzes (Judge 1999; Leuthold 1998), but the effectiveness of these techniques has not been fully assessed. For example, Gregor and Cuskelly (1994, qtd. in Agarwal and Day 1998) noted greater student participation through bulletin boards, but they do not focus on analysis of student performance.

One of the first studies of online economics instruction (Vachris 1997) again found no significant difference between student performance in an online Principles of Macroeconomics class and in a traditional lecture setting. More recently, Harter and Harter (2004) examined student performance in an introductory economics course over four semesters, introducing a class Web page and online quizzes in the second semester of data collection. The technology enhancements did not improve performance on multiple-choice questions, after controlling for a variety of students' background characteristics.

However, other studies did report on improved performance in online environments. Agarwal and Day (1998) measured the value added of a "partial" online learning experience in undergraduate principles and graduate courses that used supplemental e-mail, online exercises, and class discussion lists. They found that the "partially online" students performed significantly better on concept questions added to the final exam and suggested that the Internet enhancements worked better for students with higher initial GPAs. Navarro and Shoemaker (2000a) found that online learners perform better than traditional students in a macroeconomics principles class. In their case, multimedia CD-ROMs containing video, audio, and text lectures were used as the principal online delivery instruments. They compared the results of both online and traditional students on 15 short essay questions included in the final exam.

Sosin et al. (2004) constructed a large database of introductory economics students across several institutions. Although a wide range of technology enhancements were considered (e.g., class Web pages, PowerPoint, e-mail), online-only courses were not included. Overall, the use of technology significantly improved students' performance; however, women continued to perform worse than men in economics, and the students' self-reported GPA had a significant impact in raising test scores. The authors suggest that factors affecting students' choice of classes with technology enhancements may be linked to their observed performance.

A contradictory result was reported by Brown and Liedholm (2002), who compared performance in microeconomics principles courses across three teaching modes: traditional lecture, online video lecture, and a hybrid course consisting of traditional lectures supplemented with online assignments. Although online students had higher GPAs and ACT scores, they scored significantly lower on a common set of multiple-choice questions. However, female students did perform a bit better in the online setting, suggesting that the gender gap in economics might be reduced by the use of online instruction.

Anstine and Skidmore (2005) addressed the student self-selection issue in an analysis of MBA students taking statistics and managerial economics classes.

Students in their sample chose between entirely online classes and traditional in-class formats. Although the online students started the semester scoring higher on both the GMAT and a class pretest, they performed significantly worse on take-home exams: a simple regression analysis indicates a 5 percent penalty associated with the online environment, after controlling for students' background characteristics. They found that the average student performed worse in the online class, even after controlling for endogeneity between choice of learning environment and learning outcomes. They also found little effect of gender on either course selection or performance, an issue to which we pay attention in this study. Anstine and Skidmore's analysis concerns graduate-level courses; we focus here on the link between course selection and performance in introductory economics.

A NEW EXPERIMENT AT CSUF

In this study we analyze academic performance of students who enrolled in multiple sections of Principles of Microeconomics at California State University, Fullerton. Some of the sections were offered as online classes using basic, easy-to-use Internet tools rather than multimedia technologies. As we discuss in detail in the next section, most students were able to choose enrollment across different offerings of the principles class, so comparison of student performance between online and traditional courses assumes each student has sorted according to his or her comparative advantage. However, our students, like those in most U.S. baccalaureate institutions, are not "specialized" online learners. They take few courses online and a larger number of classes in a traditional lecture format. Given the high cost of living in the area, many students work one or more jobs in addition to attending classes.

Specifically, we attempt to address some of the questions raised by Navarro and Shoemaker (2000a, 2000b), and by Brown and Liedholm (2002), on whether students in introductory economics courses perform better online, and whether student background characteristics (and gender) have an impact on their academic performance as well as on their choice of learning mode. Furthermore, in our analysis, we follow Anstine and Skidmore (2005) to address the issue of course selection bias and the possibility that hidden factors affecting a student's choice of instruction mode may ultimately affect performance in the class.

Research and Course Design

We taught eight sections of Introductory Microeconomics across four consecutive semesters (Fall 2001, Spring 2002, Fall 2002, and Fall 2003), each semester using two alternative modes of instruction, hereafter referred to as the online mode and the hybrid mode. The first semester represented a learning experience for the instructors and was removed from the sample. As detailed in the following paragraphs, although the instructional methods used for the control and the test groups had many features in common, they differed by design in the degree to which they used online technology. Thus, we did not take a pure test of traditional lecture teaching against online teaching; rather, we compared the in-person classroom experience with minimal computer supplements (common in many universities relying on low-tech teaching tools) with an almost completely online experience.[1] In addition, the online classes (relying on chat rooms) tended to be smaller in size than the hybrid classes (typically with 38 students) as online teaching was, at the time, a new phenomenon on our campus, which led to section sizes not being equalized. However, dropout rates remained similar in the different modes.[2]

Overall, we taught economics principles to 156 students across the three semesters, with 58 students enrolled in the online sections and 98 students enrolled in the hybrid sections. Across semesters, and within each mode of instruction, the groups were similar in size; for all groups, we adopted the same textbook, the same course content, problem sets, and exam format (but different questions each year). The same online support and instructional technology (Blackboard Course Info 5.0) were used to create course Web sites for communication through posting of class information and material, class announcements, and e-mail. Each online section of the class met in person only three times, for examinations, whereas the hybrid class met face-to-face for 2.5 hours per week.

Some evidence suggests that instructors with a comparative advantage in teaching online tend to select that mode of instruction (Navarro 2000). To avoid instructors' self-selection issues, and because only one online section of the course was offered by the department each semester, we alternated in teaching the Internet course. To minimize instructor bias, we selected the same textbook, assigned the same readings and problem sets, used the same lecture notes and the same exams, and shared any other material relevant to the course. Additionally, during each semester of instruction we coordinated the sequence in which topics were covered, as well as the timing of exams, assignments, and so forth.

We administered a confidential entry survey to all students in the first week of instruction. We also obtained permission to access students' records on the online SIS+ university database, from which we collected information on GPA, transfer status, and course load when entering the class. These data allowed us to control for selection bias, and to isolate the effect of the instructional technology on students' performance.

The key aspects of the course designs are presented in Appendix A. The hybrid course involved weekly, face-to-face lectures for about 90 minutes, a minimal class Web site, and hands-on computer lab assignments for roughly another 45–50 minutes per week. The online course involved an expanded Web site. Students used the Internet to access online study guide problems and used various other Internet resources to complete the lab assignments. Course content was delivered entirely in the virtual environment, with students using the weekly chat sessions for content clarification. Sample problems were completed together in the synchronous chat sessions. We graded chat room attendance and participation alike, ensuring some feedback for the students between the posting of lecture notes and the group discussion times.

Appendix B lists the evaluation instruments used. Exams constituted about 75 percent of each student's final grade, and we allowed students to drop the lowest of the three open-book quiz scores. Each in-class, proctored examination contained the same questions for both the online and the hybrid course. All answers were graded from common keys and using the same point allocation across questions.

Analysis of Class Composition and Students' Entry Characteristics

We present the statistics regarding students' personal characteristics (see Table 1) and their academic background (Table 2). The raw data show that the online students were on average older than the students in the hybrid group. Whereas both groups had a much-older student who was more than 50 years of age, the age distribution demonstrates youth tending toward the hybrid group. Eighty-five percent of the hybrid students were 23 years old and younger, compared with 47 percent online. The online group had a higher proportion of married students with children, and these variables were highly correlated with student age. There were more female students in the online group than in the hybrid group, and they traveled longer distances to campus. More students in the online courses had taken an economics class before, but they had taken less calculus. The online group also reported working more hours per week and studying longer hours than the hybrid group. With regard to declared majors, the hybrid group had a higher proportion of business majors than the online group. Our tests indicate that statistically significant differences existed between class groups for most measures, with only a few notable exceptions (distance traveled, parents' education, math background, and semester of enrollment).[3]

Gender differences also emerge regarding some of the relevant background characteristics. Females in the online class were more likely to be married with children, and their parents were better educated. Women were also earning a wider variety of majors, worked more hours off campus, and studied longer. There was no significant difference in student GPA across genders, yet the female students had less calculus background than the men and tended to have enrolled in economics previously.

Does Online Learning Improve Performance? Analysis of Summary Statistics

Table 3 presents the summary statistics for the performance measures. We list the individual exam means because, although all students in our sample completed the final, not all attempted all of the earlier tests.[4] No statistical significance emerged for the earlier in-class exams, but the online group and hybrid group did diverge on the final examination. Specifically, the raw data suggested that the online learners performed significantly better on the final. There were some differences across semesters, which are accounted for in the econometric analysis. Namely, the final exam scores from the first semester (Spring 2002) mirrored the pattern in Table 3, whereas in the second semester there were few differences between the two groups, and in the third semester of our data both groups of students performed worse than previously, although the gap between the online and hybrid groups remained present.

TABLE 1. Definitions and Summary Statistics of Personal Characteristics

Variable	Online group ($n = 58$)		Hybrid group ($n = 98$)		Test statistic			Male ($n = 79$)		Female ($n = 77$)		Test statistic		
	M	*SD*	*M*	*SD*	χ^2	*t*	*p*	*M*	*SD*	*M*	*SD*	χ^2	*t*	*p*
Age (years)	25.31	6.92	20.73	4.12		5.18	.0000	21.97	5.28	22.91	6.21		1.01	.31
Male (%)	36		59		7.70		.0055	—		—				
Distance to campus (miles)	19.04	10.84	16.42	9.52		1.56	.12	16.39	10.49	18.42	9.67		1.24	.22
Married (%)	29		6		14.68		.0001	13		17		0.56		.45
Children (%)	21		4		10.92		.0010	9		12		0.34		.56
Work per week (hours)	29.20	14.67	22.27	10.64		3.38	.0009	24.10	12.63	25.61	12.80		0.73	.46
Study per week (hours)	12.75	8.72	10.14	7.95		1.83	.07	10.49	7.88	11.81	8.78		0.95	.35
Parent with a college degree	74		67		0.80		.37	65		75		2.15		.14

TABLE 2. Definitions and Summary Statistics of Academic Characteristics

	Online group ($n = 58$)		Hybrid group ($n = 98$)		Test statistic			Male ($n = 79$)		Female ($n = 77$)		Test statistic		
Variable	*M*	*SD*	*M*	*SD*	χ^2	*t*	*p*	*M*	*SD*	*M*	*SD*	χ^2	*t*	*p*
Previous economics (%)	59		40		5.19		.0228	39		55		3.67		.0554
Cumulative GPA (4.0 scale)	2.85	0.57	2.57	0.60		2.89	.0045	2.65	0.59	2.69	0.62		0.42	.67
Business major (%)	48		73		10.05		.0015	68		60		1.26		.26
Completed college calculus (%)	33		39		0.57		.45	42		31		1.89		.17
Completed college algebra (%)	76		81		0.49		.48	75		83		1.66		.20
Semester 1 (%)	31		34		0.12		.73	37		29		1.17		.28
Semester 2 (%)	33		37		0.25		.62	35		35		.002		.96
Semester 3 (%)	36		29		0.73		.39	28		36		1.30		.25

TABLE 3. Summary Statistics of Assessment Outcomes

	Online (n = 58)		Hybrid (n = 98)			
Variable	*M*	*SD*	*M*	*SD*	*t*	*p*
Midterm 1	73.51	11.59	72.34	14.44	0.52	.600
Midterm 2	59.02	16.93	59.43	17.30	−0.14	.880
Final exam						
Total	68.11	13.83	61.65	16.77	2.48	.014
Semester 1 (n = 51)	71.58	12.34	60.42	16.55	2.73	.005
Semester 2 (n = 55)	72.16	14.64	69.47	13.83	0.66	.260
Semester 3 (n = 50)	61.48	12.24	53.34	16.43	2.00	.030

TABLE 4. Scores by Gender and Instruction Mode for All Semesters

	Male (n = 79)		Female (n = 77)			
Variable	*M*	*SD*	*M*	*SD*	*t*	*p*
Midterm 1						
Online	77.71	12.06	71.06	10.73	2.16	.0352
Hybrid	75.39	13.49	67.88	14.79	2.57	
Total (n = 153)	76.01	13.09	69.41	13.01	3.13	.0021
Midterm 2						
Online	62.05	18.11	57.38	16.28	0.99	.3245
Hybrid	64.20	15.75	52.66	17.34	3.22	.0013
Total (n = 149)	63.62	16.32	54.99	16.88	3.17	.0018
Final exam						
Online	68.88	13.81	67.68	14.01	0.32	.7528
Hybrid	66.39	14.96	54.79	17.05	3.56	.0006
Total (n = 156)	67.05	14.62	60.98	16.86	2.40	.0174

Interesting performance trends emerge in Table 4 when we compare scores across gender and modes of instruction. Straight comparisons of the exam scores across gender lines show significantly lower scores for women. In theory, online education can lessen the gender gap in economics by either lowering male performance or by improving female performance in those sections compared to the hybrid class. Our results suggest the latter. Although women received fewer total points than men in both online and hybrid courses, over the semester the gender gap (in exam points) was significantly reduced in the online group, but it persisted in the hybrid group. The online class shows no significant difference in the female and male scores on the final examination, and, in fact, the online females outscore the males enrolled in the lecture/hybrid classes. Our results follow Brown and Liedholm (2002), yet suggest a weaker possibility of the distance-learning environment being especially favorable to female students.

ANALYSIS OF PERFORMANCE ACROSS MODES

In this section, we consider how the teaching mode affects performance, controlling for many other students' characteristics. We use an endogenous switching regression model to address the effects of students' self-selection across modes. We consider whether the trends in students' mode choice and performance are jointly determined, and we use the results to predict how exogenously assigned students would perform in different types of classes. Overall, we demonstrate the importance of student GPA and class semester in determining student outcomes. We also find that women and men had different experiences across teaching modes.

Possible Links between Teaching Mode Selection and Student Performance

Economics departments usually offer multiple sections of the principles classes, and we assume that students can choose the section that best meets their needs. The ideal section may vary by time, instructor, or type of teaching method. In this study, students had the opportunity to choose between a regular economics principles class and the online version when they registered in advance of each semester. As the literature suggests, many factors could lead a student to prefer an online class: working, living farther from campus, childcare responsibilities, or past problems learning economics in a traditional class, to name a few.

Tangible links between teaching mode choice and class performance are likely. As a worker's self-selection into an appropriate job choice can improve his or her welfare (Roy 1951), students who can self-select into the teaching mode appropriate to their human capital or location characteristics should also perform better in an economic principles course and achieve other family and work-based goals. We recognize that students often include other concerns (e.g., family, work) in class section choice, so that utility maximization is their ultimate goal.

Examining the Interlinked Selection and Performance Results

A basic econometric choice framework is needed to measure the impact of teaching mode on student performance while taking into account the problems of student heterogeneity and class selection processes. We rely on the framework proposed by Maddala (1983) for program evaluation and self-selection. The general fitted estimates for analyzing exam score performance caused by the treatment of online education (without selection bias) would be:

$$Y = \begin{cases} Y_f = \alpha_f + \theta' M + B_f' X + \varepsilon_f & \text{(a) } (\textit{full sample}) \\ Y_1 = \alpha_1 + B_1' X + \varepsilon_1, \quad \textit{if } M = 1 & \text{(b) } (\textit{for participants}) \\ Y_0 = \alpha_0 + B_0' X + \varepsilon_0, \quad \textit{if } M = 0, & \text{(c) } (\textit{for nonparticipants}) \end{cases} \tag{1}$$

where α is a parameter to capture the constant scores in each teaching mode (1, 0, or f), B_1 is a parameter vector of regressors for students in the online mode, B_0 is a parameter vector of regressors for students in the hybrid teaching mode, B_f is a parameter vector of regressors for all students, M is a dummy variable that captures the teaching mode ($M = 1$ online), θ is a parameter to capture the effects of teaching mode on overall performance, and ε represents the error term.

Equation (1a) represents a single equation intercept shift model that keeps the slopes of the coefficients the same across both teaching modes. Equations (1b, 1c) allow the slopes and the intercept effects to vary between the online and hybrid classes (Anstine and Skidmore 2005). Performance could be related to the selection between the online and the hybrid teaching modes. M is a dummy variable that takes the value of 1 if the student enrolled in the online class and 0 in the hybrid section. Although the process of each student's class selection M^* based on utility maximization is unobservable, the actual outcome M is observed and related to a series of variables Z as[5]

$$\begin{aligned} &M = 1, \quad \textit{if } M^* > 0 \\ &M = 0, \quad \textit{if } M^* < 0 \\ &M^* = b'_m Z + w \quad \text{(participation decision function)}, \end{aligned} \tag{2}$$

where Z includes variables in X and additional regressors. However, the OLS estimates of equation (1) may be biased if some correlation exists between the error terms ε and w. In other words, the test score observed is conditional on the values of the teaching mode selection equation. To address this concern, equations (1b, 1c) and (2) can be estimated as a joint endogenous switching system using Full Information Maximum Likelihood methods;[6] the cross-equation error correlation terms, ρ_{w1} and ρ_{w0}, indicate the significance of the endogeneity for each subsample (i.e., $\text{Corr}[w, \varepsilon_1] = \rho_{w1}$; $\text{Corr}[w, \varepsilon_0] = \rho_{w0}$). Alternatively, an extra selectivity correction term (incorporating the error correlations) is placed in the performance regressions in a Heckman two-step method (Heckman 1979). Whether outcomes in the online teaching mode are significantly different can be initially seen in the dummy variable of equation (1a) as the single equation model of Table 6 and in the differential returns to the explanatory variables in (1b, 1c) as the switching regression model. We also work with the predicted performance of students across modes.

However, we only observe the performance of online-choice-type students who took an online class and the performance of hybrid-choice-type students who took a hybrid class. In general, when students cannot enter the section they desire, and they are rationed into a less-desirable teaching mode, lower performance or utility, or both, may occur. Students may be observed in the online teaching mode because all the hybrid sections of principles were closed. (During the period of our study, the new online sections were never closed because of high enrollments.) In examining the registration database of matched student identification numbers, we determined that less than 20 percent of the students in the early semesters did not enter their first-choice (hybrid) economics section because it was already closed; a small subsample (eight students) of late registrants were forced to take an online class. There were no significant differences in the background characteristics of those students who enrolled in their hybrid choice mode and those who could not, except regarding their hours worked.[7] Here we have a natural experiment to observe students' outcome in a setting that could determine suboptimal performance. However, the differentials in the process of sorting could also be related to unobserved problems that students faced because they registered late.

Econometric Terms and Results

Although we collected data on all quizzes and exams, we focus on the mandatory final exam score as measure of student cumulative knowledge of the class. In addition, focus on the final avoids problems associated with the quizzes and earlier exams with the inclusion of students who later dropped. The results in Tables 5 and 6 use variables described in Tables 1 and 2 to explain why students ended up in the online section ($M = 1$) and the factors behind student performance (measured as points on the final exam).

We examine selection in a univariate probit framework in Table 5. We hypothesize that older students possess more maturity and discipline and that they gravitate to online learning. Also, women with children could need more time flexibility so that the variables "kids" would be positive with "male" negative. A greater distance from campus should increase online enrollment probability as should a greater number of hours worked. Because many students in our university are first-generation college enrollees, we also include parent college completion

TABLE 5. Univariate Probit Online Mode Selection for the Maximum Likelihood Estimation

	Specification 1[a]			Specification 2[b]		
Variable	Coefficient	*SE*	Marginal effects	Coefficient	*SE*	Marginal Effects
Constant	−4.28**	1.00		−4.54**	0.97	
Age	0.05*	0.03	0.02	0.07**	0.03	0.026
Male	−0.32	0.26	−0.12	−0.24	0.25	−0.13
Distance	0.02*	0.01	0.009	0.02*	0.01	0.01
Kids	0.55	0.53	0.21			
Hours worked per week	0.04**	0.01	0.01	0.035**	0.01	0.01
Parent with college degree	−0.07	0.30	−0.03			
Previous economics	0.85**	0.28	0.31	0.79**	0.27	0.29
Cumulative GPA	0.74**	0.23	0.28	0.68**	0.22	0.25
Business major	−1.05**	0.30	−0.39	−1.035**	0.29	−0.39
Completed college calculus	−0.12	0.28	−0.05			
Semester 1	−0.09	0.32	−0.03			
Semester 2	−0.29	0.31	−0.11			

Note: Type I error levels. [a]Log-L = −67.62; $\chi^2(6, N = 149) = 63.03$, 75% observed correct. [b]Log-L = −68.75; $\chi^2(6, N = 149) = 60.75$, 77% observed correct.
$^{*}p < .10$. $^{**}p < .05$.

TABLE 6. Final Exam Performance Maximum Likelihood Estimation Results

	Single equation model[a]				Switching regression model[b]					
	Whole sample		Selection equation		Online		Hybrid		Switching equation	
Variable	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*
Constant	3.90	10.95	−4.15**	1.16	10.92	23.55	−16.46	16.32	−4.18**	1.25
Online	−8.77	5.87								
Age	0.80**	0.32	0.07**	0.03	0.68	0.65	1.22**	0.31	0.08**	0.03
Male	4.15	2.75	−0.35	0.26	−2.70	4.17	7.58**	3.77	−0.47**	0.26
Distance			0.03**	0.01					0.025**	0.01
Hours worked	0.16	0.11	0.03**	0.01	0.07	0.13	0.35*	0.20	0.03**	0.01
Previous economics	−0.32	2.77	0.75**	0.30	−0.26	4.76	0.43	3.88	0.80**	0.30
Cumulative GPA	12.10**	2.55	0.59**	0.24	9.63*	4.05	15.77**	3.26	0.48*	0.26
Business major			−1.07**	0.29					−0.93**	0.25
Semester 1	8.56**	2.64			9.80**	4.16	5.44	3.74		
Semester 2	12.95**	2.75			12.11**	3.72	11.57**	3.80		

Note: Type I error levels. [a]Log-L $= -652.24$, $\sigma = 13.58^{**}$, $\rho = 0.66^{**}$, $N = 149$.
[b]Log-L $= -645.63$, $\sigma_1 = 11.82^{**}$, $\sigma_0 = 15.94^{**}$, $\rho_{w1} = 0.64^{*}$, $\rho_{w0} = 0.94^{**}$, $N = 57, 92$.
$^{*}p < .10$. $^{**}p < .05$.

as a signal of likely student motivation to enroll online. We also add academic characteristics that might affect the propensity to choose an online class. Here we explore whether students with a higher GPA, strong math background (calculus), and a planned business major are more likely to enter the online sections. We expect those having taken economics previously may opt for the online section to repeat a failed class or to build on their experience. We explore enrollments across the semesters as online education received more publicity (the third semester dummy is omitted because online enrollments were noticeably higher and scores lower).

Table 5 shows that students' personal characteristics and human capital together influenced their choice of class type. In the longer model (specification 1), males were 12 percentage points less likely to choose the online option, and each year of age increased the online probability by about 2 percentage points. Even apart from having children and a heavier workload, older students may possess the maturity necessary for online education. Distance from campus affects choice even though many students still needed to commute to campus for other classes. Those with heavier job demands and more hours worked almost always selected an online course. Business majors (perhaps those with more insight on the best and worst hybrid course instructors) were highly unlikely to choose the online option. We find no semester effects in the students' choice pattern. Those who had previously had some economics principles class were nearly 31 percentage points more likely to experiment with the online class. And a student's GPA has some effect on sorting, with the academically successful students 28 percent more likely to choose an online class.[8] Specification 2 presents a moderate-sized specification including the most significant variables that we focus on below.[9] Gender is considered because we expect women to prefer the convenience of online education, and we do find this term significant in the joint maximum likelihood estimates (MLE). Few differences are observed across the specifications, although the role of age in the online option increases.

Two variables in the selection process (distance and business major) were omitted from the final exam score equation for identification of a possible endogenous switching model. We feel these are valid variables to remove for identification because they should affect a student's choice of class mode yet not their performance in it; student residency location should not matter, and the mixed business and social science content of Economic Principles makes it appropriate for students of many different majors. Standard chi-square tests demonstrate that the variables are significant predictors and that they are uncorrelated with the error term in the test performance equations although correlated with the class mode selection.[10]

Thus, in the second equations we explore whether age (+), gender (−), work hours (−), previous economics (+), GPA (+), and semesters (+) are likely to change test scores apart from the teaching mode (with our expectations in parentheses). We include the semester dummies in Table 6 to control for the reality of different tests offered each term;[11] however, because the standard practice underlying the Roy model is one in which the regressors Z in the selection equation include all variables in X, we estimated that separately.[12] We focus on whether students' choices across teaching regimes could be inside the structure of the model with links between the unobservable factors affecting both selection and performance (the correlation between w and ε), suggesting an endogenous switching process.[13]

Table 6 presents the estimates of the final exam scores for the full sample single equation model, and each subsample of students with selectivity corrections in a switching regression model.[14] The MLE switching equation (specification 2) did not vary substantially from the univariate probit results of Table 5, apart from the evidence that males are less likely to choose the online class. Neither a semi-log nor Tobit specification of the dependent variable (final exam points) provided an improvement in fit, nor did interaction terms in the performance regressions (e.g., age, gender). The initial view of the full sample, single equation model shows student performance is affected by age, academic background, and class semester. Similar to Agarwal and Day (1998), we find good students continue to do better than mediocre ones. A student's acquired knowledge—measured through their previous GPA—significantly raises the final exam score by more than a full letter grade. Older students also enjoyed a performance premium. After controlling for these factors and assuming equal slopes across class modes, the online dummy barely misses being significantly negative ($p = .14$). However, this result constrains the returns to background characteristics to be equal across modes.

Some differences in the online and hybrid class subsamples appear on the right side, which allows for mode slope effects. Although the two subsample performance equations miss being significantly different and the data better fit a single equation, a few important differences are worth noting.[15] We find students receive different returns to their personal characteristics depending on which class mode they take. There appears to be a higher return to GPA and age in the hybrid class, and males in the hybrid sections see a significant increase of nearly a grade (7.5 points) compared to females. The semester effects are more relevant in the online subsample: student performance increased significantly as the online class sections became more standardized (or instruction improved) across time.

To further explore how observable student personal characteristics affect performances across modes, we ran a full interaction single equation model allowing both the intercept and slopes to vary across the online and hybrid modes. This specification, presented in Table 7, demonstrates that the online class in itself (through the intercept) is not significantly negative; the gender slope effects for the online group are more important. We ran a separate regression to focus only on the most significant differences in the subsamples (the gender interaction effects), setting the slopes of the other terms equal across subsamples; under this scenario, we find important gender differentials by class mode. Namely, males receive a full grade worse on the final exam in the online class.

Selectivity bias is present. The positive correlation coefficient ρ_{w1} suggests positive sorting for those students who chose the online class; a significant positive relationship exists between the *latent* factors affecting the probability of entering an online class and how those factors affected the final exam scores. But the positive ρ_{w0} for the hybrid group implies negative sorting; some hybrid-type students could have received a higher return to their latent factors, and performed better than an average person, in an online class had they enrolled there. These

TABLE 7. Interaction Model of Final Exam Maximum Likelihood Estimation Results

Variable	Sample 1[a] Coefficient	Sample 1[a] *SE*	Sample 2[b] Coefficient	Sample 2[b] *SE*
Constant	−10.26	14.87	−0.22	10.85
Online	10.61	20.14	−6.27	5.20
Age	1.04**	0.31	0.82**	0.30
Age × online	0.24	0.71		
Male	8.02	3.25	8.18	3.14
Male × online	−11.67**	4.97	−11.78**	4.60
Hours worked	0.28	0.18	0.17	0.11
Hours worked × online	0.28	0.18		
Previous economics	−0.16	0.19	0.17	2.90
Previous economics × online	0.04	3.43		
Cumulative GPA	14.40**	2.92	12.98**	2.47
Cumulative GPA × online	−3.54	4.82		
Semester 1	6.51**	3.41	7.90**	2.55
Semester 1 × online	3.27	5.81		
Semester 2	12.36**	3.45	12.27**	2.69
Semester 2 × online	−0.73	5.27		

Note: Type I error levels. [a]Intercept and all slope effects of online mode; Log-L = −646.86, $\sigma = 13.95^{**}$, $\rho = 0.79^{**}$.
[b]Intercept and only significant slope effects of online mode; Log-L = −648.43, $\sigma = 13.93^{**}$, $\rho = 0.77^{**}$.
$^{**}p < .05$.

hidden characteristics of the students in our sample could have improved student performance in the online mode.[16]

The restrictive single equation specification in Table 6 suggests nearly similar final test scores across the two teaching modes. To verify this, we next consider predicted learning outcomes using the MLE coefficients for each subsample in Table 6. The average predicted final exam score for each subgroup in their actual class is not that different (63.51 points online and 67.70 hybrid, for an approximately 4 point gross gap). But predicted scores, controlling for endogeneity, are different than observed scores; a student with the average characteristics of the whole sample would receive 59.66 points online and a significantly higher amount, 71.5 points, in the hybrid class ($t = -18.43$).[17] And students would perform differently if placed in a different class setting than what they had chosen. We find the online-choice type student would receive a higher final score of 77.78 in the hybrid class ($t = 11.97$). A student with the average hybrid-type characteristics would receive 10 points less in the online class ($t = -14.19$). We note that the effect of the demographic differentials within each mode is quite strong, but, in general, the students with online-type characteristics always do significantly better in any type of class. Their initially higher GPA and older age benefit them in all class settings, yet their returns to these characteristics are higher in a hybrid class.[18] This trend is consistent as we exogenously vary two important student background characteristics across a range of possible scenarios.[19]

In sum, we find a negative penalty associated with online teaching for most students. The endogeneity of the selection process could explain the opposite exam score trends of Table 3. Stronger students chose the online mode and hence increased the mean in those sections. Returns to students' latent factors (not included in the regression) suggest a premium to the online class and may explain why some did select that option. However, returns to important human capital endowments of each student—age and GPA—are higher in a traditional setting so that the stronger students could have done better there. The only exception remains along some gender variations; younger female students with low GPAs would not do any better in the hybrid setting.

Finally, Table 6 also provides an opportunity to view the effects of sorting against student preferences. We consider the predicted performance of the special students in both modes using the MLE regressions results in Table 6. Here we find the students who did not self-select into their preferred hybrid mode were penalized significantly. The given demographics of this group suggest low performance in any class (their actual average final exam score in the online sections was only 57.13 points); however, we predict their final exam scores would be 61 points in the hybrid class yet only 52 points online ($t = -2.81$). Thus these students likely could have performed better in a traditional class setting had there been sections open to accommodate them. This highlights the importance of student self-selection and the need to balance the availability of class sections of different modes in introductory economics.

CONCLUDING REMARKS

We find that the virtual classroom environment, when compared with a hybrid setting (a lecture section with some Internet supplements), has a complex impact on the performance of students taking introductory economics classes. Although the raw data suggest improved performance of online students, our controls for the endogenous selection process point toward an insignificant or even negative effect. Our findings echo both those reported on the popular "No Significant Difference" Web site, and by Vachris (1997) and Anstine and Skidmore (2005), yet would not support other studies of economics showing strong improved online outcomes (Agarwal and Day 1998; Navarro and Shoemaker 2000a, 2000b).

Under a variety of specifications we find that older, working women are more likely to choose an online class. Good students with a high GPA, those who had previously taken economics, and nonbusiness majors consistently opted to try the online economic principles class. Major and GPA variables exerted the strongest marginal effect on class selection. Most students entered their first choice of class section and teaching mode.

In this study, the students' choices (based in part on latent variables) did result in higher raw exam scores on average for those who actually selected that mode; in particular, female students improve significantly in the online setting. We control for semester effects because the same exam was not offered each term; this trend appears in two of the three semesters included. However, controlling for other factors, we then find no significant difference on the final exam scores of students enrolled in the online sections under a restrictive specification not allowing for differential returns on the explanatory variables. We barely reject the hypothesis that two different regression processes occur in the online and hybrid teaching modes. For the online subsample of students, semester effects were crucial alongside GPA. In the more traditional hybrid mode, male students continue to enjoy an advantage over female students. Separately, we consider only the significant factors affecting mode performance; in this scenario the male students could do worse online (see Table 7). Thus we find the gender gap may be reduced by online education, both by the fact that men receive a higher differential in the hybrid and lecture-based setting, and that women do better in an online setting.

We highlight the important, and significant, endogeneity of class mode selection—students choose a class section based on factors that the researcher can and cannot see. We find evidence of positive sorting for the online subsample and negative sorting for the hybrid subsample; latent student characteristics should have assisted them in performing better online. But we also exogenously assign students across modes and use the coefficients of the subsample regression to consider if they could have done better in a different class mode than what they actually chose. This process shows that most students would have performed best in the hybrid class, given various levels of observed performance variables. The finding that factors not included in our regression favor the online setting stands in contrast to lower returns to important explanatory regressors (age and GPA) in that mode. Of the observed factors that influenced selection, only GPA, age, and male gender significantly increased performance (particularly in the hybrid mode), suggesting that students more likely followed both a utility maximization and a comparative advantage rationale in their decision making.

Overall the teaching effectiveness of the online class mode improved in the middle semesters of our experiment. This suggests that it could be of value to perform repeated studies in institutions that have managed online classes for a decade or more. Online class delivery may offer a solution to distance education in economics; however, we would note that its cost-effectiveness is not proven here as the online classes had lower enrollment than the hybrid sections, given the imperfect administrative adjustment process that affected enrollments in the early years. In designing our study, we chose to limit ourselves to easy-to-use, accessible, and relatively simple Internet tools, whereas other studies included multimedia presentations that used video, digital sound, animated photo images, and interactive graphs, for highly sophisticated content delivery. Wider competition in the principles market could lower the cost of these supplements over time.

NOTES

1. We examined the online economics offerings at several large, state, Tier II and Tier III institutions, and community colleges. We found that the majority of these institutions use simple online tools in a course format similar to ours. The options range from online students being offered computerized or cable television links to simultaneous campus lectures, followed by online quizzes (done at

several California state universities) to the posting of online lecture notes and quizzes, with weekly asynchronous discussion boards, being offered at other California, Washington, and Midwestern institutions. Anstine and Skidmore (2005) used an online program involving PowerPoint slides with an audio overlay recorded on a CD-ROM. Our class format, combining online lecture notes with weekly synchronous chat rooms, was not widely observed elsewhere.

2. We consistently had a smaller number of students enrolled in the online sections compared to the hybrid sections during the years of our study. Course administrators were unable to equalize section numbers by reducing the number of sections because the university had made a commitment to offer online sections each semester as well as regular sections at odd hours; in addition, many students at our university are commuters with heavy workloads, so class sections were rarely viewed as perfect substitutes. In recent years, demand for online classes has increased so that section sizes have equalized.
3. Data on SAT scores could not be obtained for all students.
4. The raw data show that online learners performed better in multiple-choice, open-book short quizzes, with the differences being statistically significant in the first two quizzes. We do not report or analyze quiz results because the quizzes were administered differently across the two modes and there was no instructor's monitoring of the online group while they were taking the quizzes.
5. The Roy model (Roy 1951) typically assumes the selection equation M relates to the perceived differences in earnings (or performance) across modes, the X variables in equations (1b, 1c), and additional cost of entry or nonpecuniary effects received in a given mode, or both. In this case, as discussed below, we eliminate some variables from X in the estimation of Z to ensure convergence yet mention the full results separately.
6. For a discussion of the switching regression model with endogenous switching, see Maddala (1983) and Anstine and Skidmore (2005).
7. The special subgroup worked an average 13 hours weekly, compared with 22 hours from the remaining hybrid-choice type students; this amount is significantly lower with a t statistic of -2.03.
8. California State University measures grades on a 4-point scale, with 4 being the highest— "A." GPA is calculated as the mean of each class grade weighted for the class credits.
9. The reduced specification 2 is not significantly different from the longer specification 1 in Table 7; the likelihood ratio statistic of 2.27 is less than the $\chi^2(.95, 5)$ critical value of 11.07.
10. In a separate probit, we include only business major and distance and find both variables highly significant individually, with a joint $\chi^2(2) = 14.23$, $p = .000816$. We use an over identification test (Wooldridge 2003, 534) on our two excluded variables by using the residuals from the test performance equation in an auxiliary regression. The test statistic $nR^2 = .884$; this is less than the 5 percent critical value of $\chi^2(1) = 3.84$, $p = .1881$. Thus, we fail to reject the null hypothesis that at least one of our excluded variables is uncorrelated with the exam performance residual ε.
11. We find that we can accept the null hypothesis that the coefficients on the semester dummy variables are 0 in the selection equation. The Log-likelihood of the restricted probit with zero coefficients on the semester effects (Specification 2 of Table 7) is -68.75, while the log-likelihood of an unrestricted probit is -68.27. This provides a likelihood ratio test statistic of 0.96, well below the $\chi^2(0.95, 2)$ critical value of 5.99.
12. In separate calculations, we did include the semester dummy variables in both the selection and performance equations and found this model did not converge in the maximum likelihood estimates. The two-step Heckit estimators (the starting values for the MLE process) provided nearly identical estimates of the final exam performance in the Switching Regression Model in Table 6; the only changes noted were a significant positive effect of age for the online subsample and a significant premium for both semesters for the hybrid subsample.
13. We considered a Hausman test as performed elsewhere (Hausman 1978; Duncan and Leigh 1985; Anstine and Skidmore 2005) and found less evidence of endogeneity because the predicted values of our probit equation (2) were not significant predictors in the full-sample performance equation (1a) estimated by ordinary least squares (OLS). However, we consider this full sample test less appropriate because it does not indicate whether selection is occurring in only one class mode (Duncan and Leigh 1985); we find evidence of strong endogeneity appears for the smaller online subsample, but this is less significant for the hybrid group, when estimated by the Heckit two-stage method.
14. We estimated the endogenous switching results in Limdep, with the summary statistics of Tables 1–4 calculated using E-Views.
15. We estimated a full sample model without the mode dummy with a log-likelihood of -653.33. This compares with the subsample log-likelihoods of -645.63. This provides a likelihood ratio

test statistic of 15.4, which just misses being significant compared with the chi-squared statistic of 15.51 for 8 degrees of freedom at the .05 Type I error level. Using a Chow test on the pooled and separate sum of squares in the Heckit two-step (and OLS) regressions, we calculated F statistics of 2.21 and 1.45, which cannot reject the hypothesis of equality at the .05 Type I error level with 136 and 9 degrees of freedom.

16. In our two-stage Heckit results preceding the MLE estimations of Table 6, we find a positive mean and a positive coefficient on the λ term for the online group whose average product is 6.6 points; for the hybrid group, the negative mean and the positive coefficient on the λ term gives an average product of -4.6 points.
17. Because the students measured across two modes represent nonindependent, matched pairs samples, we consider a test of the significance of the means of the difference as outlined in McCall (1986, 232).
18. We decomposed the predicted gross gap of -4 points associated with the online class into an effect caused by the returns at the mean in a class mode $(B_1 - B_0) \times X_0$ and the effect caused by different background mean factors $(X_1 - X_0) \times B_0$. The first component summed to -10.35 and the second 5.67, suggesting the penalty of the online regime outweighed the stronger background characteristics of the online students.
19. We held all other background characteristics of the students constant yet varied their gender, age, and GPA across two extreme levels (age at 20 and 40 years; GPA at 2 and 4). For men, the youngest, lowest GPA students would earn 50 points in an online class compared with 62 in the hybrid class; raising their GPA to 4.0 raises their scores to 69 and 93 points, respectively. The oldest male students with a very low GPA would still perform better in the hybrid class (63.5 points there, compared with 86 online), with extreme scores of 83 points in an online class and 118 points in hybrid class for older students with a 4.0 GPA. The trends are the same for women with a 4.0 GPA, yet the youngest women with a 2.0 GPA would earn 53 points online and 54 in a hybrid class.

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APPENDIX A
COURSE DESIGNS

Differences in course design are presented in bold type.

Online course ($N = 58$)	Hybrid course ($N = 98$)
Textbook and companion Web site with online study guide	Textbook and companion Web site with online study guide
Instructor Web site for announcement, posting of relevant material, and grades	Instructor Web site for announcement, posting of relevant material, and grades
Online lecture supplements	**Face-to-face lectures**
Weekly online chats and mandatory online participation	
Weekly computer lab assignments	Weekly computer lab assignments
E-mail	E-mail
Electronic testing: online quizzes	**In-class quizzes (open book)**
In-class midterms (2) and final exam	In-class midterms (2) and final exam

APPENDIX B
PERFORMANCE EVALUATION INSTRUMENTS

- Common Instruments
  - Three quizzes (online for online students only)
    - Common multiple-choice questions
    - Open books and notes
  - Two in-person exams
    - Common format and content
    - Multiple-choice, true or false, and essay questions
  - In-person final examination
    - Common format and content
    - Cumulative, with more emphasis on last third of course
    - Multiple-choice, true or false, and essay questions
    - Weekly computer lab assignments
- Online Course Only
  - Weekly online chat and online participation
  - Extra credit discussion board postings
- Hybrid Course Only
  - Extra credit attendance points