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Efficiency in the Use of Technology in Economic Education: Some Preliminary Results

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This paper reports preliminary results of a project funded by the Andrew F. Mellon Foundation that is intended to ascertain whether technology-enhanced introductory economics courses are more effective and also more efficient than traditionally taught courses. Blecha's (2000) survey of faculty at different types of institutions of higher education documents that economics instructors now use a continuum of technological enhancements ranging from e-mail, web sites, presentation software, computerized games, and spreadsheets to computerized instruction and distance learning. While several studies investigate the consequences of using technology on student performance, there has been little attempt to compare the efficacy and efficiency of the various types of available technologies.

I. Relevant Studies and the Database

Economists typically analyze the impact of instructional innovations by testing for signifi-

cant differences in student performances between a test and control course using a production function explaining student performance.¹ Using this approach, one set of findings shows that some uses of technology perform as well or better than conventional methods (Richard Hannah, 1996; Linda Manning, 1996; Agarwal and A. Edward Day, 1998). Another set suggests that the benefits of technology may not be uniform across student abilities, course levels, course types, or gender (Margaret A. Ray and Paul W. Grimes, 1992; Bartlett and Susan Feiner, 1992; N. Scott Cardell et al., 1996; M. O. Borg and H. A. Stranahan, 2002; Byron W. Brown and Carl E. Liedholm, 2002). Although it is often asserted that using technology takes more time, we are not aware of any systematic comparisons of the time costs of using different technologies across a large number of instructors and courses.

To address efficiency and effectiveness issues, we construct an extensive database of 67 sections of introductory economics enrolling 3,986 students, taught by 30 instructors across 15 institutions during the spring and fall semesters of 2002 (see Table 1).² Of the institutions, six are Doctoral/Research, six are Masters, and

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¹ The production-function approach is not without problems and critics (William E. Becker, 1997). The production function measures only one part of student's decision-making system. Also, data loss and sample selection bias from pre to post test can be substantial as students drop the course or miss tests (Becker and William B. Walstad, 1990; Becker, 1997). A single multiple-choice test is unlikely to capture the multiple products, such as attitudes and self-confidence, that might be created by teaching innovations.

² All instructors received permission from the Institutional Review Boards of their institutions, and all students who participated provided signed consent forms. Data were collected in such a way that students were assured of confidentiality, including privacy relative to their instructors except for the TUCE scores.

TABLE 1—SUMMARY OF SAMPLE CHARACTERISTICS

Semester	Courses	Instructors	Schools	Students ^a
Spring 2002	31	21	11	1,224
Fall 2002	36	24	15	2,270
Both semesters	67	30 ^b	15 ^b	3,494

^a The database has 3,986 consenting students, of whom 3,494 completed the course.

^b Instructors and schools were counted only once if they participated both terms.

TABLE 2—PARTICIPANTS BY TECHNOLOGY LEVEL AND TYPE OF COURSE

Semester	Total courses	Technology level	
		Tech	Not tech
Spring 2002	1,224	680	544
Fall 2002	2,270	1,365	905
Total number	3,494	2,045	1,449
Percentage of total	100	58.5	41.5

Semester	Type of course		
	Macro	Micro	Combination
Spring 2002	999	178	47
Fall 2002	1,565	639	66
Total number	2,564	817	113
Percentage of total	73.4	23.4	3.2

Note: The table includes only students who consented and completed the course.

three are Baccalaureate, according to the Carnegie classifications. We include pairs of high- and low-technology courses within institutions. We note in particular that all of these courses represent at least some face-to-face interaction; pure distance-learning courses are excluded from our data. Table 2 shows the breakdown of students by technology level and course content (micro- or macroeconomics) for both semesters. The database includes the following items: pre- and post-course TUCE student scores, student surveys detailing attitudes toward economics, perception of instructor and technology effectiveness, instructor surveys regarding use and perception of technology, weekly course time diaries for the instructors, Myers-Briggs Type Indicators for instructors and students in selected courses, and two weeks of student study-time data.

TABLE 3—KUDER-RICHARDSON POSTTEST RELIABILITY

Sample	Macro	Micro
CEUTT	0.66	0.82
Norm	0.76	0.80

II. Analysis of Student Performance

We begin by addressing the effectiveness of the various instructional technologies. We use a fixed-effect panel model to control for cross-sectional differences among institutions. The measure of student performance is the difference between the post- and pre-course scores on the Test of Understanding College Economics (TUCE). The TUCE is the only nationally normed measure for this purpose, making it the obvious choice for a student performance measure. Nonetheless, criticism of the TUCE has generated two concerns: it is 12 years old, and it does not test higher-level cognitive abilities.

To address the first of these criticisms, we conduct an analysis of student responses to each of the TUCE questions. Using the six criteria suggested by the TUCE authors to compare our sample's responses to the 1991 norming responses, we find troubling differences.³ Table 3 reports the Kuder-Richardson coefficient of reliability to demonstrate the extent of these differences. We use factor analysis to identify eight questions from the macro TUCE that perform poorly, and we eliminate them, leaving 22 questions (macdif22) to measure performance in macroeconomics.⁴ All but one of the 30 micro TUCE questions (micdif30) perform well in a factor analysis, so we do not modify the microeconomics measure. The second concern is the ability of the TUCE to test critical thinking skills using learned economic concepts. While this concern may be relevant to assessing our results, we agree with Becker's (2001 p. 7) conclusion on the controversy surrounding the TUCE: "As this debate continues researchers have no choice but to use the available content tests or consider alternatives of yet more subjective form."

³ A separate paper describing the TUCE analysis is available from the authors upon request.

⁴ The eight questions eliminated from the macro TUCE are 4, 5, 10, 13, 17, 19, 26, and 30.

TABLE 4—INDEPENDENT VARIABLES USED IN THE MODEL

Variable	Definition
Technology	class in which extensive electronic technology is used: 0 = no, 1 = yes
Powerpoint	instructor uses PowerPoint regularly: 0 = no, 1 = yes
Emailmaterials	instructor emails materials to students: 0 = no, 1 = yes
Courseware	instructor uses courseware (WebCT, Blackboard, etc.): 0 = no, 1 = yes
Talkins	number of times student talked to the instructor outside of class
Hoursweb	number of hours student browsed the web per week
Emailins	number of times student e-mailed instructor during the semester
Highschcalc	student took calculus course in high school: 0 = no, 1 = yes
Collegecalc	student took calculus course post-secondary: 0 = no, 1 = yes
GPA	GPA at the beginning of the class as reported by students
Gender	gender variable: 0 = men, 1 = women
Hoursjob	student hours of work per week
Hourscredits	student credit hours currently enrolled
Classsize	initial class size (beginning of semester)
Semester	Spring 2002 = 0, Fall 2002 = 1

The independent variables used in the model are listed in Table 4. The variable Technology is coded as 1 if the course uses technology extensively, and 0 otherwise. While this dummy variable is dichotomous, there exists significant variation in the types of technologies used, both between and across the high- and low-technology pairs of courses. Accordingly, information from the surveys is used to construct the additional measures of the types of technology used (see Table 4). Because different technologies are at the discretion of the instructors and students, we develop separate instructor and student measures. Clearly, instructors are best suited to report on the technologies that they use in class (e.g., black/whiteboard, PowerPoint), or development of web-based material (e.g., use of courseware, web pages). Similarly, students are best suited to report on their own use of technologies (e.g., e-mail instructor, talk to instructor, hours on the web, etc.). We code the dummy variables representing the use of individual technologies from the instructor and student surveys accordingly. Student surveys also provided data on the number of times or hours that students use technology for communication and learning.

TABLE 5—FIXED-EFFECT PANEL REGRESSION WITH INSTITUTION CROSS GROUPS

Independent variable	Dependent variable			
	macdif22	micdif30	macdif22	micdif30
Technology	0.541*	0.646 [†]		
Powerpoint			−2.467*	−3.515*
Emailmaterials			−0.993*	2.908*
Courseware			1.952*	−1.324
Talkins			−0.096	0.025
Hoursweb			−0.031	−0.176*
Emailins			0.078*	0.002
Highschcalc	0.099	0.741*	0.010	0.659 [†]
Collegecalc	0.730*	−0.206	0.792*	−0.141
GPA	0.752*	0.427*	0.720*	0.381 [†]
Gender	−0.053	−0.594 [†]	0.032	−0.643 [†]
Hoursjob	−0.018 [†]	−0.003	−0.013 [†]	0.005
Hourscredits	0.073*	−0.040	0.081	−0.056
Classsize	−0.005*	−0.001	−0.001	−0.039*
Semester	0.331	−0.348	0.644*	−0.425
Constant ^a	0.254	3.483*	0.431	6.800*
<i>R</i> ²				
Within	0.051	0.032	0.080	0.074
Overall	0.046	0.001	0.113	0.003
<i>F</i> statistic	11.150*	2.250*	8.930*	3.050*
<i>N</i> , observations	1,884	637	1,465	558
<i>N</i> _{<i>i</i>} , cross groups	12	10	12	10
<i>σ</i> _{<i>u</i>} cross groups	1.389	2.892	1.836	4.179
<i>σ</i> _{<i>e</i>} overall	3.563	3.860	3.491	3.821
<i>Rho</i> ^b	0.132	0.360	0.217	0.545
<i>F</i> statistic, all <i>u</i> _{<i>i</i>} = 0	13.12*	21.98*	7.89*	17.99*

^a STATA reformulates the results of fixed-effect panel regression so that the reported intercept is the average value of the fixed effects (see <http://www.stata.com/support/faqs/stat/xtreg2.html>).

^b Fraction of variance due to cross groups, *u*_{*i*}.

[†] Statistically significant at the 10-percent level.

* Statistically significant at the 5-percent level.

The regression results are shown in Table 5. The effect of the aggregate technology variable is positive and significant in both the macro and micro courses. The size of the difference is less than one question, or about 2.1–2.5 percent of the total scores. The results for our technology-type variables are noteworthy. The use of PowerPoint is negative and significant in both courses. Some individual technologies have different impacts depending on course content. In macro courses, the coefficient on e-mailing materials is negative and significant, while that for using courseware is positive and significant. In micro courses, however, the coefficient on e-mailing materials is positive and

significant, while that for use of courseware is not significant. Students in macro who e-mail the instructor experience a slightly larger performance gain, but performance suffered for students who spend more time browsing the web, particularly for microeconomics courses, where this variable is negative and significant.

Among the control variables, consistent with other studies, the GPA coefficient is positive and significant in these models. Since this variable is self-reported, measurement error is likely (Nan L. Maxwell and Jane S. Lopus, 1994).⁵ As a robustness check, the coefficients are reestimated without using the GPA. The Technology coefficient remains positive and significant. In addition, preliminary estimates using separate technology variables for the top and bottom 10 percent of the GPA distribution suggest that the performance response to technology may be stronger for high- and low-ability compared to average-ability students, as also found by Ray and Grimes (1992).⁶

A prior high-school calculus course has a positive and significant effect for micro, while taking a college level calculus course is found to have a positive and significant effect for macro. Taking a previous economics course is not found to be significant in any regression, and it is thus omitted in the final model. Regarding the role of gender, we find that women's performance increases significantly less than men's in the micro regressions, but the hypothesis of no difference is not rejected in the macro regressions. We follow the recommendation of Becker and John R. Powers (2001) that initial enrollment be used as a measure of class size to accommodate concerns pertaining to withdrawal and selection bias. We find, consistent with other recent studies (Becker and Powers, 2001; James Arias and Douglas M. Walker, 2004), that the coefficient of the class-size variable is always negative—and it is significant for

macro in the model using Technology and for micro when using the individual technology variables.

The number of hours students work competes for their study time. Working more hours has a significant negative effect on student performance in macroeconomics courses but is insignificant for microeconomics. The arguments regarding student credit hours are more complex. Enrollment for fewer credit hours implies less time competition from other classes; however, lower credit hours are also likely to be associated with part-time students who have heavier external time obligations. We find that taking additional courses improves performance significantly in macroeconomics courses when using the dichotomous technology variable but is otherwise insignificant.

Econometric models of the production of learning may have estimation problems related to measurement, self-selection, data censoring, and endogeneity (Becker, 2001; Becker and Powers, 2001). We have attempted to address some of these issues in the current models, and others are planned for future research. For instance, the data-censoring problem arises if the dependent variable has an upper or lower bound that limits the measurements of student performance. The difference between the pre and post TUCE has a possible minimum of -30 and maximum of $+30$ for the micro test and -22 to $+22$ for the revised macro test scores. The observed differences in the TUCE scores range from -9 to $+20$ for micro and from -7 to $+19$ for macro. The mean and median differences in TUCE scores for the micro courses are 4.7 and 4, for non-tech and tech respectively, and 3.6 and 3 for the macro courses. While we acknowledge that these scores are not continuous, they do not seem to be truncated by the upper and lower limits.

Our preliminary single-equation estimates on this new unique data set are very interesting; however, endogeneity and self-selection issues are a priority for future research. The results reported here do not control for selection problems that may occur because students self-selected themselves into certain courses or failed to participate in some of the study instruments. Furthermore, a simultaneous-equation approach might be more appropriate. For example, students having difficulties with the course may spend more time in the instructor's office,

⁵ The production-function model is misspecified without a student-ability variable (John J. Siegfried and Walstad, 1998; Becker, 2001). Ideally, the model should include an independent measure of ability, such as SAT or ACT results, or GPA as reported by the registrar. Unfortunately, because of strong legal concerns about privacy at many universities, it is often difficult for researchers to collect these data. One procedure used when outside ability data cannot be collected is to ask students to report their GPA.

⁶ Estimation results are available from the authors upon request.

send more e-mails, or spend more time on the course web site because they need extra help.

A challenge for studies of teaching innovations using test and control classes is the difficulty of separating innovation effects from instructor effects. In addition, the possibility cannot be dismissed that the nonrandom nature of our sample of instructors may be responsible for some of our findings. For example, the self-selected nature of the instructors may have produced a group of technology users with a stronger interest in the project than some of the non-technology instructors. For these reasons, we have more confidence that the multiple technology-use variables, compared to the single Technology variable, reflect technology effects rather than instructor effects. These specific variables include technologies used in both the technology and non-technology courses. Finally, we are controlling for the unobserved heterogeneity that may result from pooling across diverse institutions by our use of fixed-effects regressions.

III. Preliminary Description of Instructor Time Use and Costs Data

Turning to issues of efficiency, we provide a brief description of instructor time use and costs. Our data do not support the often-voiced contention that using technology takes more time on the part of instructors. We do have some cases in our instructor pairs where this is true, but in general, the effort expended by technology-using and non-technology-using instructors follows no general pattern. It is important to note that we adjust for class size in making our pair comparisons. However, there are interesting differences in the incidence of the time used. Specifically, technology-intensive instructors are more likely to expend time on nonteaching days, evenings, and weekends than their lower-technology peers.⁷ We also see a tendency in large classes for higher-technology instructors to spend more time on exam preparation and less time on the actual grading relative to their lower-technology peers, in part because they build online quizzes and exams and rely on the technology to do the grading.

⁷ A separate paper describing the protocol for gathering time-cost data is available from the authors upon request.

Interestingly, our data also show that the choice to use or not use technology in teaching Principles has been blurred by the institutionalization of information technology. E-mail is now a normal means of communication for many students. Lower-technology teachers may use WebCT or Blackboard to post materials and assignments if there are strong institution guidelines to do so. The choice is also very individualistic. Some higher-technology instructors make extensive use of PowerPoint. Others do not. Some instructors make extensive use of all the features of WebCT, while others do not. Finally in terms of types of costs other than time, we found that none of the instructors in our sample required any special funding to conduct their courses. All used existing university investments in infrastructure and software.

IV. Conclusion

Using a database collected from 30 instructors and their students at 15 institutions over two semesters, we conduct a preliminary investigation of the impact on student performance of teaching with technology. The major objective of this project is to examine the costs associated with technologically enhanced instruction and the benefits in terms of student performance. Using institutional fixed-effects regressions, we find that technology usage, as measured by a dichotomous variable comparing classes using extensive technology to those using little technology, has a small but positive impact on student performance. More importantly, our results using separate variables for various types of technology use indicate that some uses enhance student performance and others do not. Likewise, different uses have different effects for micro- and macroeconomics courses.

The preliminary analysis of instructor costs suggests that technology and non-technology instructors spend about the same amount of time, but with substantial differences in when and how that time is spent. Our results suggest that it is no longer appropriate to define instructors as either technology-using or non-technology-using. The analysis of time costs and technology usage indicates that the issues no longer concern whether to use or not use technology, but what technology to use in what manner. We have just begun to explore the many avenues of research that our data set will provide, and we will have

much more to say on these issues in future papers.

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