A Meta-Analysis of Technology
Interventions in Collegiate Economics Classes

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Abstract: Technological interventions in and out of the classroom have been sold as a way to improve student understanding of economics for decades. Yet despite the panoply of ways to incorporate technology, it is not clear which types of interventions consistently result in statistically significant improvements in learning outcomes. Of 145 papers devoted to the technology in collegiate economics courses over the past 30 years, less than one third attempt to quantitatively assess the impact of technology on student learning outcomes. Of the regressions reported in these studies, 60 percent find a positive relationship between a technology intervention and a student-learning outcome; however, in only 42 percent of the regressions is the relationship statistically significant. Considering the literature with meta regression analysis suggests (a) no technology intervention routinely results in improved learning outcomes across studies; this is despite evidence of (b) publication bias that favors papers with statistically significant results. We conclude that success improving student-learning outcomes with technology interventions is highly individual. As a field, economics needs more well-designed, large-scale studies of technology interventions.

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1. Introduction

Technological interventions have long been sold as a way to improve student engagement, retention, and learning. Economics instructors have explored everything from illustrative Excel simulations (Barreto 2015; Mixon and Hopkins 2008; Moini 1996; Strulik 2004), to interactive games (Lange and Baylor 2004), to online homework managers (Lee, Courtney, and Balassi 2010; Rhodes and Sarbaum 2015), to Twitter reminders to study for quizzes and exams (Al-Bahrani and Patel 2015). In response to growing demand, the *Journal of Economic Education* (*JEE*) made the decision to allocate a portion of each issue to online teaching resources. Arguing that "online technology has the potential to revolutionize teaching and learning," the *JEE* committed to documenting and highlighting "the best and most innovative Web sites for teaching economics" (Sosin and Becker 2000). However, despite a panoply of technologies and ways to incorporate them into economics courses, there is little clarity as to which types of interventions yield the greatest returns and which are more trouble than they are worth. Such weighing is particularly important because teaching innovations and pedagogical changes are often time consuming; in the face of high opportunity costs and uncertain outcomes, economics instructors may default to traditional lecture (Allgood, Walstad, and Siegfried 2015).

Sosin (1999), Sosin and Becker (2000), Goffe and Sosin (2005), and Allgood, Walstad and Siegfried (2015) qualitatively surveyed the voluminous literature on teaching economics with technological interventions. We add a quantitative dimension to these surveys with a meta-regression analysis of the impact of technological interventions on student learning outcomes. We examine articles published from 1990 through 2018 in economics journals indexed by EconLit, with JEL Codes A22 (Economic Education and Teaching of Economics: Undergraduate) or I23 (Higher

Education, Research Institutions), and which report on the use of technology as related to the teaching of collegiate economics. Our primary question of interest is whether there is convincing evidence that technological interventions can improve student cognitive performance in economics courses. Therefore, we include only studies that incorporate some technology in post-secondary economics course and for which we can identify a dependent variable measuring some aspect of learning. These studies are are a significant minority of what is published on technology in the classroom, as most report on 'cool ideas' but without quantitative assessment. Our effort to identify the types of technological interventions which are consistently associated with statistically significant gains in learning outcomes illustrates both the challenges of using technology effectively and the difficulties documenting student learning in economics.

2. The Literature on Technologies, Computers, and Learning in Economics

Over the past three decades, one of the best sources of information on the teaching of economics has been the National Survey of Teaching Methods in Undergraduate Economics Courses (Watts and Becker 2008; Watts and Schaur 2011).[1] Survey responses have consistently indicated that economists have a decided preference for "chalk and talk" lecturing. However, the use of technology-assisted learning has increased significantly over the period. Comparing the results of the first three National Survey of Teaching Methods in Undergraduate Economics Courses, Watts and Becker (2008) find that introductory economics instructors were notably more likely to employ Power Point slides (22 percent to 5 percent), to use the computer lab (9 percent to 4 percent), to employ computer-simulated games (4 percent to 2 percent), and to require database use or internet

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[1] The survey was given for the first time in 1995 and has since been updated quinquenially. They survey is mailed to 3000 to 4000 academic economists identified from various professional mailing lists. The response rate has varied between 7.9 percent and 19.1 percent. Watts and Becker note that faculty more interested in teaching were likely more willing to fill out the survey, and thus responses may be considered to represent the "front line" of teaching changes.

searches (19 percent to 3 percent) in 2005 than in 1995. The results were similar for intermediate theory courses. In statistics and econometrics courses, instructors also employed Power Point, computer lab work, and internet searches at increasing rates (Watts and Becker 2008, 275 – 277). As Watts and Schaur (2011) reported on the Fourth National Survey, use of PowerPoint, move clips, computer lab assignments, and internet research all increased, albeit slightly (the median responses remained that technologies were only "rarely" and "occasionally" used). Watts and Schaur added new categories for the use of "clickers or other response devices" (~ 6 percent) and for computer simulations (~ 8 percent). Using the same survey data, Harter, Schaur and Watts (2015) found instructors at undergraduate and masters' degree granting institutions were statistically significantly more likely to adopt teaching strategies other than straight lecturing, as compared to instructors at PhD granting institutions. Most, however, still relied primarily on lectures. The authors concluded that "use of computer displays also increased, no doubt reflecting changes in technologies, classroom setups, and capital support…the use of workbooks is shrinking – possibly due to online substitutes provided by publishers or instructors" (Harter, Schaur and Watts 2015, 1181).

Allgood, Walstad and Siegfried (2015) surveyed the literature on teaching economics to undergraduates, including the use of technology in and out of the classroom. "The usual reason for adopting alternative methods," they argued "is to get students actively engaged in the learning process because a traditional lecture class is viewed as too passive a form of instruction" (Allgood, Walstad and Siegfried 2015, 299). Sosin (1999) suggested that the active engagement encouraged by technological innovations had the potential to expand interest in economics to underrepresented groups, particularly to women. University administrators were early converts, pushing faculty to integrate computer applications into economics courses (Owen 2007)

However, despite an ever-growing diversity of technological interventions, it is not clear that they enhance student *learning* – as distinct from student engagement or student preferences. Several

studies documented that students perform worse in online courses than in live classroom settings (Brown and Liedholm 2002; Coates *et al.* 2004; Pyne 2007). Carter and Emerson (2012) found no evidence that online experiments improved student course performance. Neither Kennelly, Considine and Flannery (2011) nor Hernández-Julien and Peters (2012) identified differences in exam performance between students who completed paper homework assignments and students who completed online homework assignments. Rankin and Hoass (2011) were unable to document any advantages, measured by student course grades, from the use of Power Point slides. Students with access to online quizzes did not perform any better on exams than students without access (Harter and Harter 2004). When videos of lectures were made available for student re-watching online, student performance on exams did not improve (Savage 2009).

Sosin *et al.* (2004) examined 67 sections of introductory economics enrolling nearly 4000 students across 30 instructors and 15 institutions, and where each institution was represented by pairs of high and low technology sections. Student cognitive gains were measured as the difference between pre- and post-Test for Understanding and Comprehension in Economics (TUCE) scores. They found students in high technology sections gained about one question over their comparable peers in low technology sections. However, in their efforts to examine the impact of specific types of technology applications, the results were highly mixed and inconclusive.

Negative findings should not lead us automatically to reject technological interventions. Empirically verifying the effectiveness of teaching interventions is difficult for many reasons. For a researcher to expect meaningful differences, Allgood, Walstad and Siegfried (2015) emphasized that the treatment must be given sufficient time to work and be well conceived from the start. They argue that comparing a similar intervention across institutions can be challenging because implementation may vary by instructor, course, and university. Measuring gains to learning is further complicated by difficulties in achieving random samples and in clearly measuring outcomes (student

knowledge, student interest, student learning). Standard measures of economics course performance may not be able to capture the impact of the intervention, or students may convert gains in learning to leisure time, satisficing on grades. "Given the difficulties of designing a controlled comparison and the challenging econometric issues, it should not be surprising that there has been a limited amount of research on the effectiveness of different methods of teaching economics, despite the passionate advocacy for many of them" (Allgood, Walstad and Siegfried 2015, 299). We note an additional complicating factor – changing technology and technological improvements means that it is difficult to compare ostensibly similar interventions over time.

3. Study Design and Methodology

We use meta-regression analysis to examine the impact of technological interventions on student learning outcomes across studies. Meta-regression analysis differs from a traditional literature review in two substantive ways. First, it can remove some of the subjectivity that arises from the choice of which studies are evaluated; in meta-regression analysis, all relevant studies are included. Second, meta-regression analysis can help identify the extent to which study design, data gathering, and estimation strategies influence empirical findings (Card and Krueger 1995; Doucouliagos and Stanley 2009; Nelson 2015; Stanley 2001).[2]

3.1 Identifying a Sample

To identify which types of technology interventions are most likely to have a positive impact on student learning outcomes, we survey all journal articles as indexed by Econlit with JEL Codes

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[2] By approaching the literature differently, meta-analyses have the potential to upend traditional viewpoints. For example, Nelson's meta-analyses (2016 and 2015) demonstrated the falsity of the commonly held belief that women are fundamentally more risk-adverse than men. In the economics education literature, Johnson, Robson, and Taengnoi (2014) find that while most studies in economic education still document a gender-gap in student course performance, the gap has been shrinking over time and is much less statistically significant than commonly perceived.

A22 (Economic Education and Teaching of Economics: Undergraduate) or I23 (Higher Education, Research Institutions) published from 1990 through 2018.[3] We exclude studies completed before 1990 because computers and software operated very differently during this early period. Computer access was limited, and email and the internet had not yet been widely adopted. Online instruction, for example, only became available in 2000 (Allgood, Walstad, and Siegfried 2015, 301).

Our initial search returned more than 900 possible papers. These papers were evaluated individually to see if they met our criteria for inclusion in the study – (a) they had a technological or computer intervention in (b) a collegiate-level, undergraduate economics course. Applying these criteria resulted in 165 relevant papers. We eliminate an additional twenty papers because they are surveys that address broad aspects of computers and economics education rather than a specific intervention. For example, Navarro (2015) considered "How Economics Faculty Can Survive (and Perhaps Thrive) in a Brave New Online World." Owen (2007) outlined strategies for "Integrating Computer Applications into Economics Electives." This leaves us with a sample of 145 papers.

3.2 Technological Interventions, Cool Ideas, and Learning Outcomes

One particularly prominent type of paper is that which we classify as a 'cool idea.' These are papers that suggest an interesting technological intervention – for example, a simulation, game, social media, or pod-cast as a learning tool – but do not offer a quantitative evaluation of the impact of the intervention on student learning (78 of our sample of 145 papers, or 53.8 percent). A second type of paper are those that, rather than attempting to measure a learning outcome, choose instead to examine student preferences about technologies or the probability that students will choose to

[3] EconLit returned an initial sample of 927 articles for the search "computer or internet or phone or laptop or tablet or podcast or excel or spreadsheet or whiteboard" AND "education or university or college or higher education." Of these, most papers were eliminated because they did not address the teaching of economics at the post-secondary level or did not actually examine a technological intervention.

take another economics course (47 papers, or 32.4 percent). In the end, out of 145 papers, we identify 49 that attempt some sort of quantitative assessment of the impact of a technological intervention on student learning; 39 of these provide recoverable estimates of treatment effects.4 See Table 1.

Table 1. Types of Papers on Technological Interventions in Economics Classrooms

	Survey	"Cool Idea"	Quantitative Evaluation of Learning	Quantitative Evaluation of Student Preferences	Quantitative Evaluation of Other (e.g. likelihood to continue in economics)
Count	20	78	49	31	16

*Numbers add to more than 145 because some studies consider multiple outcomes.

The types of technological interventions are highly varied (Table 2). The most common is the use of a simulation in Excel or another software to demonstrate the workings of an economic model (72 papers, or 49.7 percent). Walrasian equilibriums, Monte Carlo experiments, the Solow Growth Model, the Permanent Income Model of Consumption and Savings, and dynamic Aggregate Supply and Aggregate Demand models are all considered. Applications of the Internet comprise the second largest category and include such things as 'hyperlecturing' (lecturing with embedded hyperlinks), use of websites such as WinEcon or MarketSim, the use of class webpages, and accessing economics resources on the Internet (e.g., the St. Louis Federal Reserve Banks's FRED).

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4 These studies are published in 21 different journals, the most common being the *Journal of Economic Education,* the *International Review of Economic Education*, the *American Economic Review*, and the *Southern Economic Journal.*
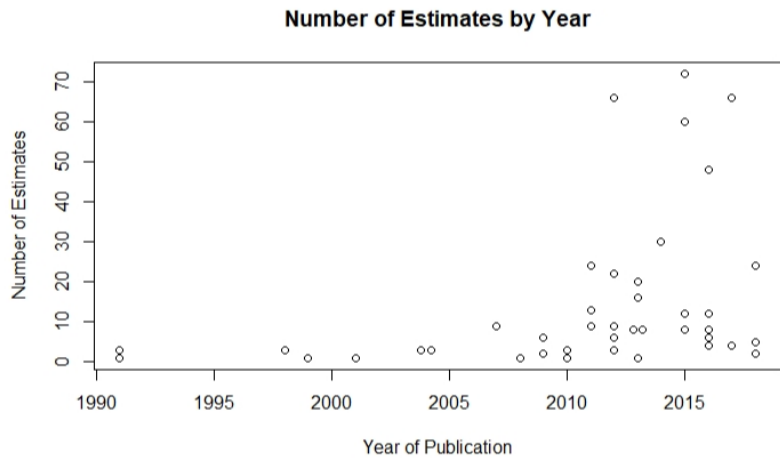
Table 2. Technological Interventions in Undergraduate Economics Courses*

Technological Intervention	Count
Accessing the Internet or use of the Internet (accessing websites, data, podcasts, or other supplemental learning materials)	41
Online or digital homework, quizzes, or exams	34
Simulations, games, or demonstrations of models in Excel or other software	72
Online course management systems (e.g. Canvas, Blackboard) and online textbooks	8
Email or social media (blogs, discussion boards, Twitter, Facebook, memes)	17
Streaming or video capture of lectures	10
Hybrid course designs (including blended and flipped classrooms)	10
Fully online courses	21
Technology in the classroom (computer lab classes, laptops in the classroom, automated response systems or clickers)	17

*Numbers add to more than 145 because some studies include multiple technology features.

The number of studies that report on the development of simulations, games, or applications of the Internet to teaching economics has been relatively consistent since 1990. Hybrid or online classes do not appear in the economics pedagogical literature until 1999. Applications of Social Media to the teaching of economics are first reported on in 2014. What is notable is that the interest in quantitatively assessing interventions in economics courses has increased substantially in the last decade.[5] Figure 1 illustrates the number of studies that attempt to estimate the impact of a technological intervention on student learning outcomes by year.

[5] As an example of this increased interest in quantitative assessments, the American Economic Association Committee for Economic Education Call for Proposals Poster Session for the 2020 annual meetings specifically requested papers "devoted to active learning strategies…[and] although we encourage presenters to include evidence that their strategy enhances learning, we do not require quantifiable evidence." https://www.aeaweb.org/about-aea/committees/economic-education/call-for-papers

Number of Estimates by Year

We speculate this increased interest in quantitatively assessing learning outcomes is at least partly

driven by the rise of behavioral and experimental economics.

3.3 Measuring the Impact on Learning from Technical Interventions

The most common strategy used by economists to evaluate the impact of instructional

innovations is to look for statistically significant differences in student performance in courses or on

exams or quizzes between treatment and control groups. Student learning is modeled along the lines

of a production function, with various individual, course, and instructor inputs contributing to

learning as an output.[6] Regression analysis captures the change in learning outcome, other input

factors held constant. Though fraught with theoretical and technical complications – including the

difficulty of generating a random distribution of students, a lack of controls for student motivation,

and the vagaries of measuring learning – this approach continues to dominate the economics

education literature (Allgood, Walstad and Siegfried 2015). As our focus is on the relationship

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[6] Siegfried (1979) explained that learning measures can be stocks or flows. Exam scores or course grade measures the stock of knowledge at a specific point in time. Gains in TUCE scores or from a pre- to a post-test are flow measures, measuring the change in knowledge over time. Studies in economic education primarily tend to be stock models.

between technological interventions and academic performance in economics courses, we do not consider studies that examine outcomes such as the impact of technology on student attendance, instructor-student communication, or student satisfaction. By design, articles that examine learning outcomes in economics but do not incorporate a technological intervention are also excluded. Last, the construction of meta-regression analysis constrains us to papers that report both an estimated treatment effect and either a t-statistic or a standard error.

In the end, we consider 34 articles examining five different categories treatment effects and 550 estimates (regressions) of their effect on student learning outcomes. We provide a complete list of these studies in the appendix. The earliest study in our sample was published in 1991 and the most recent in 2018. Considering only the sign of the estimated effect of the technological intervention, we find that 60.2 percent of regressions indicate an improvement in learning outcome. Only 41.8 percent of these positive estimates were statistically significant, however. In Table 3, we report the summary statistics for our data. The most common dependent variable chosen by the studies was student course grade followed by student performance on economics exams. The most common technological intervention in this subsample was the presence of a substantial online component.

Studies in the economics of education literature have suggested that study design can influence statistical findings (Johnson, Robson and Taengnoi 2014; Siegfried 1979). Thus, in addition to the intervention and type of dependent variable, we collect data on study characteristics such as the estimation procedure used and the presence of notable differences in effort in the design of the treatment (as an intensity measure, e.g., online versus no homework). Introductory courses are the most common type studied; ordinary least squares is the most common estimation procedure used. Despite evidence suggesting flow models are a superior approach to measuring learning gains

(Allgood, Walstad, and Siegfried 2015; Siegfried 1979), these remain uncommon in economics education studies.

Table 3. Statistical Summary of our Data

	Mean/Percent (Standard Deviation)
Dependent Variable	
Dependent Variable	
Intervention had a positive effect (= 1)	0.602
Standardized Measure of Significance of Result (t statistic)	0.812 (2.73)
Independent Variables	
Treatment Effect	
Online supplements (websites, online resources, podcasts)	0.096
Online Homework, quizzes or exams	0.365
Social media or email	0.083
Online course, hybrid course, video lectures	0.375
Use of Computers in the Classroom	0.088
Study Characteristics Variables	
Effort indicator when the intervention required a significant increase in student effort	0.382
Microeconomics Course	0.544
Macroeconomics Course	0.294
Introductory Course	0.794
Flow model of learning (as compared to a stock model)	0.154
Final course grade was the dependent variable	0.198
Exam grade was the dependent variable	0.611
Estimation Procedure	
Ordinary Least Squares	0.701
Probit	0.093
Instrumental Variables	0.027
Fixed Effects	0.044
Other	0.135
Year Paper Was Published	2011.5 (5.957)

Two methodological issues should be noted. First, we must consider that, in many cases, multiple observations are derived from a single study. While some studies report the results of a single regression (10.3%), most report multiple regression estimates, some as many as 66. Treating each regression independently would over-represent some studies. Following Bijmolt and Pieters (2001), we adopt a strategy of estimating a model with equal weights per study, where each

observation is weighted with the inverse of the total number of estimates drawn from the same study. We also cluster by study, which allows us to correct for non-independence of observations from the same study and generate heteroskedastic robust results.

Second, while we seek to measure (a) whether the technological intervention has an impact on learning outcomes, and if so, (b) the size of the impact and (c) the statistical significance of the impact, there are complicating factors. Empirical studies of learning are heterogeneous in many respects. Studies examine different learning outcomes – some studies use standardized exams such as the Test of Understanding in College Economics (TUCE), while others use a measure of course performance such as exam grade or course grade. Further complicating the issue, different estimation procedures are used across different studies, meaning that results are not defined in a common, scale-free metric. One could conceivably deal with this by standardizing by study.[7] Unfortunately, to do so requires knowledge of the standard errors of the estimated treatment effects in each study, and these are not always reported. Thus, while we initially report that 49 studies attempt to quantitatively assess the impact of a technology intervention on student learning, only 39 of these studies use regression analysis. In the end, we could only identify the necessary information in 34 of them.

4. Discussion of Results

4.1 Estimating Direction (Sign) of the Impact of Technology Interventions

As we noted, studies use different measures of learning outcome and different estimation procedures. This means estimates of the impact of a technology intervention on learning are not directly comparable across studies. Further, transformations of the dependent variable in many

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[7] For the purpose of identifying and correcting for publication bias, following Doucouliagos and Stanley (2009), we standardize by using the *t*-statistic of the estimated treatment effect, as this standardizes by precision and allows for the identification and correction of publication bias.

studies are such that we cannot 'back out' the relevant standard deviation that would be necessary to create a standardized measure of the size of the estimated coefficient on technology interventions. Instead, we define a dependent variable that is simply whether the technology treatment was positively associated with gains in the learning outcome or not.

In the regressions reported in Table 4, we examine which types or categories of technological intervention are more likely to be positively associated with student-learning outcomes. In Column 2, we consider a probit regression that is restricted to only the technology treatment effects. Column 3 reports on probit regression output that includes all treatment effects as well as a number of study control variables. The structure of our analysis necessitates assigning one of the technological treatments as the comparison case for all other interventions. We chose the grouping of online course management systems and online textbooks as our comparison case for two reasons. First, these are the most common types of technology intervention currently used by economics faculty (Allgood, Walstad and Siegfried 2015). Second, these two interventions involve a minimum effort – all other categories involve more work for both the instructor and the students.

Table 4. Technology Interventions' Impact on Student Learning

Column 1	Column 2	Column 3
Variable	**Treatment Effects Only (Standard Error)**	**Treatment Effects and Study Design Variables (Standard Error)**
Dependent Variable is the standardized estimated coefficient of the technology treatment effect		
Technology Intervention		
Online homework or quizzes	0.346 (0.699)	0.122 (0.809)
Online course, hybrid course, video lectures	-0.595 (0.725)	-1.141 (0.956)
Social media or email	-0.089 (0.708)	-0.536 (0.962)
Online supplements (websites, podcasts, games, simulations, etc.)	0.132 (0.821)	0.476 (1.069)
Computers in the Classroom	-0.278	0.568

	(0.880)	(1.081)
Study Design Control Variables		
Effort measure (technology intervention required a significant difference of effort compared to the control)		1.250 (0.498)**
Year study was published		-0.035 (0.027)
Microeconomics course		1.426*** (0.453)
Macroeconomics course		-0.860 (0.544)
Introductory level course		-1.005 (0.486)**
Flow model of learning (e.g., gains to learning over time) as compared to a stock model		1.654** (0.761)
Exam grade as the dependent variable, as compared to course grade		-0.978*** (0.330)
Standardized test grade (e.g. TUCE) as the dependent variable, as compared to course grade		-0.957 (0.685)
Male Subsample		-0.633 (0.761)
Female Subsample		-0.172** (0.594)
Estimation Procedure Used in Study		
Probit		0.658 (0.407)
Instrumental Variables		-0.912* (0.447)
Fixed Effects		-0.458 (0.419)
Other		-0.139 (0.431)
Constant	0.547 (0.701)	72.412 (55.714)
R-squared	0.395	0.341
N	550	550

* indicates statistical significance at the 10% level, ** indicates statistical significance at the 5% level, and *** indicates statistical significance at the 1% level.

The results reported in Columns 2 and 3 reflect the increased likelihood of a positive effect on learning outcome, as associated with the choice of technological intervention. A positive estimated coefficent suggests that the intervention increases the probability of finding a positive association; a negative result indicates a reduced likelihood of finding a positive association. We find

no type of technological intervention that has a statistically significant impact on the associated learning outcome. In other words, there is no category of technological intervention that is consistently associated with improved learning outcomes measured over what is found from simply using an online course management system or online textbook. Online and hybrid courses make it less likely to find a positive impact on learning outcome, as does the use of Social Media. The interventions of online homework or quizzes or online supplements are more likely to be associated with a positive impact. But, as we stated, none of these findings are statistically significant.

We do find evidence that study design influences the likelihood of finding a positive association between technology intervention and learning outcome (Column 2). Microeconomics courses are more likely to be associated with positive gains in learning outcomes than survey courses ($p = 0.002$); introductory-level courses are less likely to yield positive gains, as compared to intermediate or advanced undergraduate courses ($p = 0.039$). When exam grades are used as the dependent variable in a study, technology interventions are less likely to be successful ($p = 003$) than if course grade is used. This may be because course grades can encompass some measure of effort – homework, participation, attendance – whereas exams reflect specific student knowledge at a specific point in time. We find a similar negative effect for studies that use fixed effects estimation procedures, as compared to ordinary least squares. Perhaps most encouraging, is the statistically significant and positive association between interventions that require a substantial increase in effort and learning outcome ($p = 0.012$).

4.2 Estimating the Statistical Significance of Technology Interventions

Beyond the sign of the estimated effect of a technological intervention, we are also interested in whether the intervention had a statistically significant impact on the learning outcome. Statistical significance is consistently measured across all the studies, and is thus more easily comparable than

estimated coefficients. In Table 5, we consider which technological interventions have the largest

statistically significant outcomes, measured by the reported t or z statistic for the hypothesis test with

the null hypothesis that the technological intervention had no effect on the associated learning

outcome. Column 2 reports the results of regression considering only the categories of technological

intervention. Column 3 considers all the technology treatment effects as well as study control

variables. We continue to use online classroom management systems/online textbook as our

comparison case.

Table 5. Identifying Technology Interventions with a Statistically Significant Impact

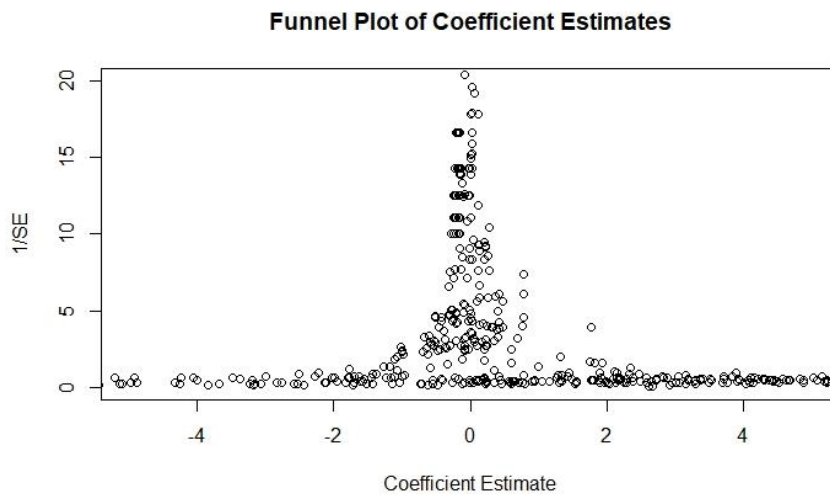| Column 1	Column 2	Column 3
Variable	**Treatment Effects Only (Standard Error)**	**Treatment Effects and Study Design Variables (Standard Error)**
Dependent Variable is the t or z statistic associated with the technology treatment effect		
Technology Intervention		
Online homework or quizzes	-0.137 (1.166)	0.537 (0.974)
Online course, hybrid course, video lectures	-1.765 (1.683)	-0.527 (1.1955)
Social media or email	-1.623 (1.670)	-0.611 (01.085)
Online supplements (websites, podcasts, etc.)	-1.060 (1.639)	0.651 (1.295)
Computers in the Classroom	-1.884 (1.893)	0.157 (1.469)
Study Design Variables		
Effort measure (technology intervention required a significant difference of effort compared to the control)		2.209 (0.873)**
Year study was published		-0.056 (0.053)
Microeconomics course		1.341* (0.718)
Macroeconomics course		-1.652* (0.888)
Introductory level course		-0.882 (0.889)

Flow Model of Learning (e.g. gains to learning over time)		1.801** (0.812)
Exam grade as the dependent variable		-1.288* (0.657)
Standardized test grade (e.g. TUCE) as the dependent variable		-1.609** (0.711)
Regression with only men		-0.429 (1.024)
Regression with only women		-1.312** (0.604)
Estimation Procedure Used in Study		
Probit		1.416 (0.883)
Instrumental variables		-0.621 (0.747)
Fixed effects		-0.277 (0.857)
Other estimation procedure		0.319 (0.713)
Constant	1.927 (1.654)	114.552 (106.437)
R-squared	0.0787	0.3120
N	550	550

* indicates statistical significance at the 10% level, ** indicates statistical significance at the 5% level, and *** indicates statistical significance at the 1% level.

We find no evidence that a particular type of technological intervention is consistently associated with a statistically significant impact on learning outcome. Online homework and quizzes evidence the smallest penalty, but for all cases, the interventions yield less statistically significant results and merely the use of a learning management system and/or online textbook. What is interesting to note is that, much like in the previous section, we find that aspects of study design are more likely to be have a statistically significant impact, compared to a technological intervention. The type of course and the type of learning outcome again stand out as important contributors to the likelihood of finding a statistically significant result.

4.3 Publication Bias and Technology Interventions

An additional methodological issue that merits discussion is the problem of publication bias. This is sometimes referred to as the 'file drawer problem', or the problem that studies which fail to find statistically significant results are less likely to be published. We first look for evidence of publication selection bias using the Funnel Graph Asymmetry Test (FAT) developed by Doucouliagos and Stanley (2009). Figure 2 depicts an approximately symmetric inverted funnel shape, which suggests that publication bias is not dramatically or obviously present.

Funnel Plot of Coefficient Estimates

To examine the possibility of bias more carefully, we consider the following equation (Doucouligos and Stanley 2009).

$$t\text{-}statistic_i = \beta_0 + \beta_1 \frac{1}{\sigma_i} + \varepsilon_i \qquad (1)$$

In equation 1, β_0 is our estimated publication bias, β_1 is our publication-bias corrected measure of the average effect of technological interventions, and ε is the error term. We find weakly significant evidence of publication bias ($\beta_0 = 0.613$ with a standard error of 0.337; $p = 0.078$). One possible explanation for this weak evidence of publication bias – as compared to the extent of bias found in

other meta-regression analyses – is that, unlike in other areas of economics, the reviewers of papers examining the impact of technological interventions on student learning outcomes are also the primary end-users of the findings under review. Since classroom interventions can be costly to adopt, and the reviewers are members of the group who would pay the adoption costs, we are incentivized to ensure that the literature holistically represents the range of possible findings.

Returning to equation 1, we find a positive and significant, but near-zero effect of technological interventions on student learning outcomes ($\beta_1 = 0.007$ with a standard error of 0.0006). This potentially suggests that, on average across all types, technology interventions have no noticeable impact on student learning outcomes. This is consistent with our findings in Tables 3 and 4. What we cannot disentangle, however, is whether there is truly no gain from technological intervention or if the near-zero effect of technological interventions is the result of students using improvements in teaching to increase their leisure consumption instead of their learning outcomes (Allgood, Walstad, and Siegfried 2015).

In consideration of the weak evidence for the existence of publication bias, we correct for publication bias using the method suggested by Stanley and Doucouliagos (2009). This method can be expanded to measure heterogeneous effects and include statistical controls. We estimate the model in equation 2.

$$t\text{-}statistic_i = \alpha_0 + \alpha_1 \frac{1}{\sigma_i} + \sum \gamma_s Z_{is} + \sum \delta_j \frac{X_{ij}}{\sigma_i} + \varepsilon_i \qquad (2)$$

In this model, the variables X_{ij} are correlated with differences in learning outcomes; Z_{is} variables are correlated with the publication selection process; α_0 is the baseline publication bias; α_1 is the bias

corrected baseline treatment effect; γ_s are the publication biases correlated with each of the controls Z_{is}; and δ_j are the bias-corrected effects of each treatment X_{ij}.

In the regressions reported in Table 6, we consider which types or categories of technological intervention are most likely to be associated with a statistically significant student learning outcome, after controlling for the presence of publication bias. In Column 2, we consider a regression that is restricted to only the technology treatment effects. This regression allows both for the possibility that different treatments may have different effects as well as be subject to different publication biases. We continue to use online course management systems and online textbooks as our comparison case.

Table 6. Technology Interventions' Impact on Student Learning

Column 1	Column 2
Variable	**Treatment Effects Only (Standard Error)**
Dependent Variable is the *t* statistic associated with the technology treatment effect	
Publication Bias Coefficient	
Online homework or quizzes	1.881**
	(0.921)
Online course, hybrid course, video lectures	0.630
	(0.587)
Social media or email	1.400
	(1.113)
Online supplements (websites, podcasts, games, simulations, etc.)	1.996*
	(1.112)
Computers in the Classroom	1.548
	(1.169)
Effect on Learning Outcomes (Coefficient)	
Online homework or quizzes	-0.003*
	(0.001)
Online course, hybrid course, video lectures	-0.054
	(0.049)
Social media or email	-0.050***
	(0.008)
Online supplements (websites, podcasts, games, simulations, etc.)	-0.392***
	(0.054)
Computers in the Classroom	-0.221***
	(0.019)

Constant	-0.466
	(1.062)
$1/\sigma_i$	0.009***
	(0.002)
R-squared	0.248
N	550

* indicates statistical significance at the 10% level, ** indicates statistical significance at the 5% level, and *** indicates statistical significance at the 1% level.

Controlling for publication bias, within the literature on each intervention, there is a small but notable bias towards reporting those results that find that technological interventions generate improvements in student learning outcomes (Publication Bias Coefficients). In the case of online homework and quizzes and online supplements this bias is statistically significant. This positive bias in publication patterns masks the true effect of technological interventions. Controlling for the bias indicates, compared to a course management system and/or online textbook, most technological interventions are associated with a small but statistically significant decrease in student learning outcomes (Effect on Learning Outcome Coefficients). Use of social media, of computers in the classroom and of online supplements demonstrate the largest negative effects.

Conclusions

There is no doubt that technology applications to learning will continue to expand in both prevalence and variety. As they do, students, university administrators, and education publishing companies will clamor for their adoption. In this paper, we attempt to provide some clarity on which types of technological interventions are most likely to be consistently and routinely associated with gains in learning outcomes, as identified through meta-regression analysis. Our conclusion is cautionary.

Over the past 30 years, 165 papers have been published that specifically address issues of technology in collegiate economics classes. Of these, 145 discuss a specific innovation. However, only a small subset of these papers of attempt to measure the impact of the innovation on learning

outcomes. In a mere 41.8 percent of regressions is the innovation associated with a positive and statistically significant impact on the learning outcome. Our meta-regression analysis confirms the ambiguous, contradictory, and inconclusive findings of this literature. Across several different specifications, we find no type of technology intervention is consistently associated with learning gains –neither the likelihood of finding a positive gain nor the significance –as compared to that yielded by the minimally invasive use of online learning management systems and/or online textbooks.

We draw several conclusions from this analysis. First, the success of technology interventions on student learning outcomes are highly individual, and cannot be attributed to any particular type of intervention. Publication bias likely contributes to our default perception that technology interventions are actually associated with better learning outcomes. Second, our inconclusive findings reflect the current, confused state of knowledge in the discipline. There is real need for large-scale, well-conceived experiments to examine the impact of technology interventions on learning outcomes in economics. Third, as we go forward with attempts to assess technology interventions, we should be sensitive to the impact of study design on the measurement of learning outcome.

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Appendix: Papers Included in Regression Analysis

Author(s)	Year	Journal
Debertin and Jones	1991	American Journal of Agricultural Economics
MacDonald and Shields	1998	Journal of Economic Surveys
Rankin and Hoaas	2001	Eastern Economic Journal
Coates, Humphries, Kane, and Vachris	2004	Economics of Education Review
Harter and Harter	2004	Eastern Economic Journal
Flores and Savage	2007	International Review of Economic Education
Dahlgran	2008	Journal of Agricultural and Applied Economics
Gratton-Lavoie and Stanley	2009	Journal of Economic Education
Savage	2009	Journal of Economic Education
Wachenheim	2009	Review of Agricultural Economics
Calafiore and Damianov	2011	Journal of Economic Education
Chen and Chen	2011	Atlantic Economic Journal
Cameron	2012	Journal of Economic Education
Carter and Emerson	2012	Journal of Economic Education
Chen and Lin	2012	International Review of Economic Education
Hernandez and Peters	2012	Southern Economic Journal
Trost and Salehi-Isfahani	2012	Southern Economic Journal
Figlio, Rush, and Yin	2013	Journal of Labor Economics
Ivan	2013	International Journal of Economic Sciences
Maclean and McKeown	2013	New Zealand Economic Papers
Self	2013	International Review of Economic Education
Harmon, Alpert and Histen	2014	International Advances in Economic Research
Aljamal, Cader, Chiemeke, and Speece	2015	International Review of Economic Education
Cosgrove and Olitsky	2015	Southern Economic Journal
Rhodes and Sarbaum	2015	American Economist
Alpert, Couch, and Harmon	2016	American Economic Review
Caviglia-Harris	2016	Southern Economic Journal
Olitsky and Cosgrove	2016	International Review of Economic Education
Swoboda and Feiler	2016	American Economic Review
Al-Bahrani, Patel, and Sheridan	2017	Journal of Economic Education
Carter, Greenberg, and Walker	2017	Economics of Education Review
Lombardini, Lakkala, and Muukkonen	2018	International Review of Economic Education
Bosshardt and Chiang	2018	International Review of Economic Education
Chevalier and Dolton	2018	Journal of the Royal Statistical Society