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The Effect of Time Spent Online on Student Achievement in Economics and Finance Online Courses

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This paper studies the determinants of academic achievement in online courses in economics and finance. The authors use the online tracking feature in Blackboard (Campus edition) to retrieve the real time each student spent in the course for the entire semester and analyze the impact of time spent online, prior GPA, and some demographic characteristics of students on final grade. Both time and GPA are significant determinants of the final grade; a higher GPA and a longer time spent online are associated with higher grades.

Keywords*: online learning, time online, academic achievement, economics and finance education*

JEL codes: *A20, A22; I21*

The number of universities in the US and abroad offering online courses has increased significantly over the past decade. The latest four surveys of the US National Center for Education Statistics (NCES) clearly illustrate this trend. In 1995, for example, about 33% of the two- and four-year institutions of higher education offered online courses; in 1997-1998 this percentage increased to 44%, and for the years 2000-2001 this number reached the level of 56% (Waits, Lewis and Greene 2003). According to the most recent survey of the NCES for the years 2006-2007, already 66% of the surveyed institutions[1] reported that they offered distance education courses (Parsad and Lewis 2008).

The online offerings of economics and finance departments follow a similar trend. For instance, in the time period 1997-2000, the number of departments offering online courses almost quadrupled (Sosin 1997; and Coates and Humphreys 2001). Given this substantial growth in the online course offerings in Economics and Finance, teaching and learning in this unique setting has become an issue that is just as important as student learning in the traditional classroom.

While there is a voluminous literature that analyzes the determinants of academic performance in traditional classes (recent studies include Romer 1993; Marburger 2001; Dolton, Marcenaro, and Navarro 2003; Kirby and McElroy 2003; Lin and Chen 2006; Stanca 2006; and Chen and Lin 2008), the contributing factors to academic success in online courses are not that well understood. Recent studies comparing the achievement of students in traditional and online courses in economics and finance generally find that online students significantly underperform their peers from the traditional classroom (Coates, Humphreys, Kane, and Vachris 2004; Anstine and Skidmore 2005; and Farinella 2007). These findings stand in stark contrast to the *no significant difference phenomenon.* This term, which became popular when Russel's (1999) homonymous book appeared, embodies the ample evidence from other disciplines that there are no substantial differences in student achievement in face-to-face and online classes. One possible conclusion economic educators can draw from this discrepancy is that we need to better understand the factors contributing to success in online courses in order to provide a quality of instruction that is on par with that from the traditional classroom.

The focus of this paper is on the effect of *real* time spent online on academic achievement in fully online courses in economics and finance. We use data capturing the actual time students spent online during an entire semester in a large public university in South Texas. The university offers online instruction via Blackboard (Campus Edition)—a virtual learning environment which keeps track of many aspects of the student activities online. We extracted the actual time students spent online per week (in minutes) and linked this measure to the grade each student earned in the course.

An important limitation of the analysis is that the login time measures only one, purely quantity rather than quality dimension of studying effort. Further, this measure is imperfect as it does not take into account the time students spent learning offline (reading textbooks, using teaching materials, etc.). Even so, we believe that our analysis adds to our current understanding of how study time affects learning in online courses as most previous studies rely on questionnaires in which students self-report the time they spent studying.

We estimated an ordered logistic model with the log-odds ratios for various grade categories as a dependent variable and time spent online (TIME), grade point average (GPA), and some socio-demographic characteristics of students as independent variables. We also included dummy variables to account for the fact that different courses are taught by different instructors.

Each course is described by a separate dummy variable, and if a single course was taught by different instructors, we added a separate dummy variable for each instructor.

The coefficients for TIME and GPA are found to be positive and significant. We perform a Wald test (see Brant 1990) to test for possible violations of the parallel regression assumption underlying the ordered logit model. This test indicates a violation of this assumption for the TIME coefficient. Therefore, we consider a generalized ordered model in which the coefficient for TIME is allowed to vary by the compared categories (A vs. lower grades, A and B vs. lower grades, etc, passing vs. failing grade). TIME has the greatest impact on the odds of passing vs. failing and the least impact on the ratio A vs. lower grades.

The ten courses considered are taught by five different instructors. There may be differences in the teaching methods and the grading procedures of the instructors that are not captured by the dummy variables we introduced for instructors. Therefore, we also analyzed the subsamples of all classes separately. Overall, the analysis of the subsamples conforms to the results obtained for the entire sample.[2]

The only study we are aware of that analyzes the effect of real time spent online on student grades in online courses is the paper by Damianov *et al* (2009). This paper uses a data sample from one semester only (Spring 2008) and pools together observations from various College of Business courses including economics and finance, accounting, marketing, management, and computer information systems. A major conclusion of this study is that if a student spends more time online than his/her peers, the student can improve his/her odds of earning D vs. F and B vs. C. The impact of time spent online on the odds A vs. B and C vs. D is positive but not statistically significant.

The present study adds several important dimensions to our understanding of the impact of time spent online. First, we use a richer data set consisting of two semesters and focus only on Economics and Finance courses. This focus allows us to address (at least to a certain extent) the problems associated with the pooled nature of the study. To control for the variation in student grades resulting from the teaching methods and the grading procedures of different instructors, we introduced dummy variables capturing the impact of the instructor. Additionally, we analyzed each data subsample (i.e. each course) separately.

A second distinguishing feature of this study is the measurement of time. We use here the absolute amount of time (in minutes) in contrast to the standardized measure of time used in Damianov *et al* (2009). This allows us to determine, the impact of, say, ten more minutes per week spent online on student performance and not the impact of, say 10 minutes per week spent online more than other students.[3]

Finally, the present study differs in its empirical strategy. The ordered choice model considered here and the extended data sample provide a more informative view of the process of grade determination and the impact of covariates such as time online on student achievement in economics and finance courses.[4]

DATA DESCRIPTION

We obtained data on all online courses offered by the Economics and Finance Department of a large public university in South Texas during the Spring and Fall semesters of 2008. Data came from two sources.

The first source is Blackboard's Campus Edition individual session log which includes a detailed track record of student activities in the online courses for an entire semester. In these courses, students in general do not meet face-to-face with the instructors. The instructors teaching online courses are either full-time tenure track or tenured faculty members who individually develop their online courses and upload them to Blackboard's Campus Edition.

The second data source contains demographic and academic information on students enrolled in these courses from the University's Office of Admissions and Records. We merged both databases and eliminated any data that could lead to the identification of an individual student or an instructor. From the initial sample of 472 students we removed those that voluntarily dropped the course before the 12^{th} day of classes. In addition, we eliminated 5 observations due to incomplete demographic data and another 13 observations because their final grade was incomplete.

The final sample consists of 438 students who received a grade in one of the 10 online courses offered by the Economics and Finance Department during the Fall and Spring 2008 semesters. Table 1 presents the descriptive statistics of our data sample. On average, almost 44 students were enrolled per online class.

There are five Economics and five Finance courses. Courses taught include Introduction to Economics, two sections of Principles of Microeconomics, two sections of Principles of Macroeconomics, two sections of Managerial Finance, two sections of International Finance, and Advanced Managerial Finance. Five different instructors taught these courses.

[Insert Table 1 about here]

Some instructors taught more than one online course in each semester. Table A1 (see the Appendix) shows that Instructor 2 taught three courses, while Instructor 1 and Instructor 3 taught the same course each semester. The remaining instructors taught one course each.

Table 2 shows the grade distribution of students enrolled in the five online Economics and the five Finance courses during the Spring and Fall 2008 semesters. The average student grade point average (GPA) prior to taking the online class was 2.80 while the average time students spent in the online courses was 2 hours and 16 minutes per week.

[Insert Table 2 about here]

MODEL SPECIFICATIONS AND RESULTS

To take into account the discrete and the ordered nature of our dependent variable (GRADE) we estimate an ordered logistic model. The empirical model is defined by the following system of equations:

$$log\frac{\Pr(i>j)}{\Pr(i\leq j)} = \alpha_j + \boldsymbol{X}\cdot\boldsymbol{\beta},$$

where $\mathbf{X} = (\mathrm{TIME}, \mathrm{GPA}, \mathrm{AGE}, \mathrm{GEN}, \mathrm{MAJOR}, \mathrm{PHRS}, \mathrm{IC1}, \mathrm{IC2}, \ldots, \mathrm{IC6})$ represents the list of explanatory variables, and $\boldsymbol{\beta} = (\beta_1, \beta_2, \ldots, \beta_{11})$ denotes the corresponding coefficients. The possible grades are A, B, C, D and F, and the variable $j \in B, C, D, F$ defines the four grade categories to be compared. We estimate a system of four equations for the following log-odds: A vs. a lower grade $(j = B)$; A or B vs. a lower grade $(j = C)$; A, B, or C vs. a lower grade $(j = D)$; and a passing vs. a failing grade $(j = F)$.

We can obtain an alternative, equivalent specification of the model which has the absolute probability of earning a grade higher than $j \in B, C, D, F$ as a dependent variable. By exponentiating the left and the right hand-side of the above equation and rearranging terms we obtain

$$\Pr(i > j) = \exp\left(\alpha_j + \boldsymbol{X} \cdot \boldsymbol{\beta}\right) \big/ \left[1 + \exp\left(\alpha_j + \boldsymbol{X} \cdot \boldsymbol{\beta}\right)\right]$$

The model is estimated by maximum likelihood. The description of the variables used in this study is given in Table 3.

[Insert Table 3 about here]

The average time spent online per student per week was in some courses significantly higher than in others. For instance, Table A1 (see the Appendix) shows that on average students enrolled in Managerial Finance (IC1) were online 2 hours and 39 minutes per week while students enrolled in International Finance spent an average of just 1 hour and 35 minutes per week.

Given that some courses have different instructors we included seven dummy variables (IC0 to IC6) to account for the differences in instruction, course content, and exams. The base category is represented by the variable IC0. Table A1 in the Appendix presents a description of these variables.

A major issue in the economic education literature has been the measurement of the impact of study time on performance. Part of the difficulties associated with this problem arises from the poor measurement of time spent on task. In this paper we are able to sidestep this issue by measuring the real time spent by students online. Our measurement adequately captures the time students actually spent on coursework because after 20 minutes of inactivity Blackboard automatically logs students off from the course.

Another important aspect concerns possible collinearities between TIME and other explanatory variables. Most notably, the GPA of students might capture not only their intellectual ability, but also their time commitment. Some good students may not need to spend much time to get a good grade, while other less able students may need to spend a significantly higher amount of time to earn the same grade. We ran several diagnostic tests to check for the presence of multicollinearity among our explanatory variables. The pairwise correlation coefficient between TIME and GPA is 0.171, and the highest pairwise correlation coefficient among any of the variables is 0.194 (between PHRS and GPA). Further, the condition index for all explanatory variables is below 1.6, which suggests that multicollinearity is not a concern in our dataset.[5]

Ordered logistic regression results

Our major findings are presented in Table 4 which shows the impact of the explanatory variables on final grade. As the variables AGE and PHRS do not appear to be of consequence for the final grade, we performed an *F* test on their joint values equal to zero. The *p* value of the *F* statistics is large (0.69), and we therefore further estimated an alternative, restricted, specification without these two variables. In the subsequent analysis, we use only the variables from the restricted model specification.

[Insert Table 4 about here]

A minute increase in TIME improves the log-odds of being in a better grade category by 0.009 when the other variables are held constant. Similarly, an increase in the GPA variable by one unit increases the log-odds of being in a better grade category by 2.246.

The coefficients for the control variables IC1, IC2 and IC5 are negative and statistically significant at the 5% level. Hence, keeping other variables constant, we conclude that students enrolled in these courses were less likely to be in a better grade category compared to the reference category (IC0). The goodness of fit measure of the ordered logit model is 0.188 which suggests that additional variables might have an impact on the probability of obtaining a certain grade. However, as Greene (2003) points out, there is a lack of a satisfactory measure of fit in models of discrete dependent variables since the maximum likelihood estimator is not chosen to maximize a fitting criterion in predicting the dependent variable (see Greene 2003, 685-686).

Generalized ordered logit model

An important restriction of the ordered logit model is that the coefficients for the explanatory variables do not vary across the category comparisons. That is, for all j, the coefficient of each explanatory variable is assumed to be the same for all grade partitions. A major problem with this *parallel lines* or *proportional odds* assumption is that it is frequently violated in applications (see Williams 2006, 60). It is often the case that the coefficients of some variables differ substantially across the comparison groups, so the ordered logit model turns out to be overly restrictive in these cases.

In this section we follow the approach suggested by Long and Freese (2006) to identify variables for which this assumption is violated, and we estimate a generalized (or partial proportional odds) ordered logit model. This model allows the coefficient for some explanatory variables to vary with the category partition but keeps the coefficients of the other explanatory variables fixed. The advantage of this model is that it is less restrictive than the ordered logit model, but more parsimonious than, for instance, the multinomial (unordered) logit model (see Williams 2006, 58).[6]

For our dataset we first use a Wald test by Brant (1990) to identify the variables for which the parallel regression assumption might be violated (see also Long 2006, 199-200). Only the variable TIME violates the parallel regression assumption at the 1% significance level (chi sq = 24.9). Therefore, for this variable we consider an alternative formulation of the model that does not impose the parallel regression constraint. More specifically, we estimate the following *generalized* ordered logit model:

$$log \frac{\Pr(i > j)}{\Pr(i \leq j)} = \alpha_j + \boldsymbol{\beta}_{1j} \cdot TIME + \widetilde{\boldsymbol{X}} \cdot \widetilde{\boldsymbol{\beta}}$$

Hereby $\widetilde{\boldsymbol{X}}$ denotes the vector of the remaining independent variables, $(\mathrm{GPA}, \mathrm{GEN}, \mathrm{MAJOR}, \mathrm{IC1}, \mathrm{IC2}, \ldots, \mathrm{IC6})$, and $\widetilde{\boldsymbol{\beta}} = (\beta_2, \beta_3, \ldots, \beta_9)$ the corresponding coefficients. Thus, except for the modification that the coefficient of TIME is allowed to vary across category comparisons, the model has the same specification as before. The results for the TIME variable are displayed in Table 5.

[Insert Table 5 about here]

The greatest effect of TIME is on the odds of passing vs. failing (coefficient = 0.0265). The coefficient declines monotonically for the remaining grade category comparisons. TIME presents the slightest impact on the ratio A vs. lower grades (coefficient = 0.0064).

It might appear that the coefficient for the various grade comparisons declines only because the number of grade categories which a student can move into becomes smaller. For instance, one might think that the comparison A,B,C,D vs. F has the largest coefficient because there are four categories which a student can move into, and the coefficient for the comparison A vs. B,C,D,F has the smallest coefficient only because there is just one category a student can move into. Observe that what matters is not only how many categories a student can move into but also how many categories a student can abandon. In the latter comparison a student can abandon four categories and in the former comparison just one. So, we cannot expect that the coefficient for one partition should be larger than another because of the model specification. This pattern is a property of the data sample rather than a property stemming from the model specification.

Effect of time spent online for selected GPA levels

To gain further insights into the effect of time spent online on student performance we analyze how an increase of the time spent online by one standard deviation (84 minutes) would affect the performance of students with different GPA levels. The results of this analysis are reported in Table 6.

[Insert Table 6 about here]

Students with a GPA of 3.0 and above increase their changes for earning an A and lower their chances of receiving any other grade. A student with a GPA of 2.0 increases her/his chances of earning A, B, and C, and lowers her/his chances of earning a D or a failing grade. We also estimated the effect of spending one more hour per week on the probabilities of earning different letter grades (see Table A3 in the Appendix). As expected, the magnitude of the change is lower but the general trend remains.

ANALYSIS OF SUBSAMPLES

As the dummy variables we introduced for course and instructor might not be able to fully control for the differences in the way instructors teach the courses and evaluate students, we analyzed the data subsamples for each course separately (see Table A1 in the Appendix for a description of the subsamples). Results do not show significant differences among the full sample and the analysis of the subsamples, with GPA and TIME significantly explaining GRADE. The only exception is the International Finance course, for which the coefficient of the TIME variable is positive but not significant. The results from the three courses with the largest number of observations (Principles of Microeconomics with 102 observations, Managerial Finance with 115 observations, and International Finance with 93 observations) are reported in Table A2 in the Appendix. Each of these courses has been taught for two semesters (Spring and Fall 2008) by the same instructor.

We have more detailed information on the grading procedure in the Principles of Microeconomics course. In this course students participate in online activities on a weekly basis. Students receive an average grade (in percentage) for each of the 13 weeks of coursework, and take a comprehensive final exam at the end of the semester. The instructor drops the week with the lowest score from consideration, and calculates the average percentage score for the remaining 12 weeks. This score is factored into the final grade with 80% and the score on the comprehensive final exam is factored into the grade with 20%. The final exam is not proctored and is asynchronous. The weekly quizzes, assignments, and postings on discussion boards that are submitted for grade are also asynchronous. One concern with this type of student testing is that it creates opportunities for students to gather at a single location and take turns in completing the exam. However, so far we have not observed that students provide identical solutions to exam problems. The reason for this might be that students are not able to get in touch with each other (not being able to regularly come to campus is a primary motivation to enroll in an online class), or that they might fear the consequences associated with cheating. The penalties for academic dishonesty at this institution are quite severe as the university strives to implement a culture of honesty. In many cases cheating leads to expulsion from academic programs and the university.

An issue related to the nature of our dataset that merits special attention is the potential existence of an automatic relationship between time spent online and grade. One could think that students who spend more time online automatically get a better grade and, conversely, students who do not log into the course get zero percent scores on the assignments they missed. These scores could directly lead to a lower final grade. The existence of such a relationship between grade and our key explanatory variable, time, would be very problematic because the association between these variables would be due to a statistical artifact rather than to the impact of time on student learning that we wish to study.

This potential problem is unlikely to be relevant for three reasons. First, students who missed assignments from two or more weeks are dropped from the course and do not appear in our sample. Second, the instructor drops the week with the lowest score, so, if a student missed the assignments in a particular week because he or she did not log into the course that week, these assignments do not affect the student's final grade. Finally, there are many course activities which students participate in (e.g., taking practice quizzes, reviewing solved practice problems, reading materials provided online such as articles from the popular press, watching short videos, taking a mock exam, reviewing the weekly feedback from the instructor, communicating with the instructor, etc.) that contribute to student learning but are not graded. The variation in our measurement of time spent online across students in our sample is almost exclusively due to these activities.

Nonetheless, to address this potential issue, we run separate OLS regressions using the overall percentage grade (Model 1) and the score on the comprehensive final exam (Model 2) as dependent variables. Using the percentage score on the final exam as an alternative measure of performance is useful here because this measure is certainly not connected to the time students spent online. On the other hand, given that the final exam counted for only 20%, students who knew that they would pass comfortably might not have taken this exam seriously. So, this performance measure might not be as accurate as the final grade, but can serve as an important robustness check for our analysis. To further compare the effect of time on these two measures of performance, we converted the percentage score students earned on the final exam into letter grades. We used then the ordered logit specification to examine the impact of time on the overall letter grade (Model 3) and on the letter grade on the final exam (Model 4). These results are reported in Table 7.

[Insert Table 7 about here]

The results indicate that the magnitudes of the effect of time spent online on the two measures of performance are similar both for the OLS and the ordered logit specification. Further, a comparison of the coefficients of time spent online for the entire sample reported in Table 4 is also very close to the coefficient we estimated for the effect of time on the final exam score (see Model 4 in Table 7).

FREQUENCY OF COURSE WEBSITE USAGE

The frequency of course website usage by students may be an alternative variable that measures the effort a student is exerting in preparation for the course.[7] The variable SESSIONS counts the number of times a student has logged into the course for the entire semester. This variable is significantly correlated with all other variables used in the analysis except PHRS. The high correlation between SESSIONS and TIME (correlation coefficient is 0.57, significant at the 1% level) suggests that both variables may be measuring student effort.

We formulated two additional model specifications: in Model S2 we included the variable SESSIONS to all the variables in the original regression, and in Model S3 we replaced the variable TIME with the variable SESSIONS in the original regression. These specifications were estimated both for the full sample (using the ordered logit model) and for the Principles of Microeconomics subsample (using OLS). We chose to report here the results from the Principle of Microeconomics subsample (see Table 8 below).

[Insert Table 8 about here]

The results for the entire sample are similar and are available from the authors upon request. It appears that the total minutes students spent in the course is a stronger determinant of student performance than the number of times a student logs into the course.

CONCLUSION

Recent research on the comparison of online vs. traditional courses of economics and finance indicates that online students underperform their peers that attend face-to-face courses. This research also suggests the existence of significant differences in the teaching and learning process in online and traditional classes. This type of evidence might lead instructors and university administrators to two polar viewpoints. One view is that economics and finance courses should not be taught online or at least we should be aware of the limitations of this delivery venue and downsize our online offerings. In particular, online classes should not be offered as a solution to physical plant capacity problems. Echoing this sentiment, Farinella (2007, 45) writes,

> "[I]t appears that the performance of students in online courses varies across disciplines and finance is not a fruitful venue for online courses."

Farinella (2007) also points to other problems related to the student evaluation of online instruction and its implications for promotion and tenure of faculty teaching online.

The alternative viewpoint is that we need a better understanding of the mechanisms of teaching and learning in online courses to be able to deliver a quality of education online that is on par with our performance in the traditional classroom. Despite recent advancements in the emerging literature on online courses in economics and finance, the gap in our knowledge of the two modes of delivery is far from being closed.

This paper takes a small step toward narrowing this gap by analyzing the impact of time spent online on student performance in Economics and Finance courses using data from a large public university in South Texas. We find that this variable is a significant predictor of performance and explore in detail how the log-odds of the various grade categories are affected. Our results suggest that online course designs and university policies designed to motivate students to spend more time online will enhance student achievement in online courses.

NOTES

[1] NCES surveyed a total of 4,200 institutions in the US.
[2] The impact of TIME on GRADE is positive and significant for all courses except for one (International Finance). For this course, the coefficient for the TIME variable is positive but not statistically significant.
[3] We would like to thank Peter Kennedy for pointing out the implications of the formulation of the independent variables for the interpretation of the results.
[4] We thank William Greene for his advice on the selection of the appropriate empirical model.
[5] For details on the tests for detecting multicollinearity consult Kennedy (2003, 213).
[6] For further details on the partial proportional odds model and other generalized ordered model specifications see Clogg and Shihadeh (1994), Fu (1998), and Peterson and Harrell (1990).

[7] We thank an anonymous referee for suggesting to look at the number of times a student logged into the course as a determinant of grade.

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APPENDIX

TABLE A1: Descriptive Statistics by Course and Instructor.

Variable Name	Course Name	2008 Semesters	Instructor ID	Class Size	Average Time	Average GPA	Average Grade
IC0	Principles of Microeconomics	Fall and Spring	Instructor 1	102	2h 32m	2.76	2.84
IC1	Managerial Finance	Fall and Spring	Instructor 2	115	2h 39m	2.69	2.36
IC2	Principles of Macroeconomics	Spring	Instructor 3	26	1h 57m	2.65	1.96
IC3	Principles of Macroeconomics	Fall	Instructor 4	28	2h 15m	2.68	2.71
IC4	International Finance	Fall and Spring	Instructor 5	93	1h 35m	3.01	3.29
IC5	Advanced Managerial Finance	Fall	Instructor 2	51	2h 04m	2.85	2.57
IC6	Introduction to Economics	Spring	Instructor 4	23	2h 29m	2.83	3.04
All courses				43.80	2h 16m	2.80	2.73

Note: Class Size refers to the total number of students taking the course. Average Time is measured in hours and minutes per week spent online. Average GPA and Average Grade are expressed on a 4-point scale. IC0 is the reference category. IC0 through IC6 are dummy variables grouping students in the same course taught by the same instructor during the Fall and Spring 2008 semesters as described in the Data Section of the paper.

TABLE A2: Estimates of the Ordered Logit Model for different subsamples.

Variable	Full Sample		Principles of Microeconomics		Managerial Finance		International Finance	
GPA	2.2669	**	2.8586	***	1.9100	***	2.6592	***
TIME	0.0091	**	0.0119	***	0.0078	***	-0.0015	
GENDER	-0.2002		-1.0956	**	0.2169		-0.0831	
MAJOR	0.4929	*	0.3503		1.2433	*	-	
FINA	0.8039	**	-		-		-	
IC1	-1.6759	***	-		-		-	
IC2	-0.8862	**	-		-		-	
IC3	0.1170		-		-		-	
IC4	0.4751		-		-		-	
IC5	-1.5276	***	-		-		-	
IC6	0.8129	*	-		-		-	
Sample size:	438		102		115		93	
Pseudo R^2:	0.188		0.244		0.137		0.135	

Notes: *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.
The dummy variable MAJOR is dropped for the International Finance subsample since this is a required course for finance majors.

TABLE A3: Effect of one hour change in time spent online on the probabilities of attaining different letter grades for selected GPA levels.

Grade	GPA = 4.0	GPA = 3.5	GPA = 3.0	GPA = 2.0
A	7.05%	12.46%	12.57%	2.92%
B	-5.55%	-8.32%	-3.29%	7.81%
C	-1.17%	-3.14%	-6.41%	1.78%
D	-0.19%	-0.58%	-1.60%	-4.11%
F	-0.14%	-0.43%	-1.28%	-8.39%

TABLES

TABLE 1: Descriptive Statistics of 438 Students Enrolled in Online Economics (Econ) and Finance (Fina) Courses During the Spring and Fall 2008 Semesters.

Class characteristic	Full Sample	**%**	Econ	**%**	Fina	**%**
Average class size (number of students)	44.00		51.80		35.80	
Average student age (in years)	24.64		24.99		24.13	
Median student age (in years)	23.00		23.00		22.00	
Total number of students	438		259	59.1%	179	40.9%
Male (number of students)	180	41.1%	102	39.4%	78	43.6%
Female (number of students)	258	58.9%	157	60.6%	101	56.4%
Hispanic (number of students)	393	89.7%	230	88.8%	163	91.1%
Non Hispanic (number of students)	45	10.3%	29	11.2%	16	8.9%
Full-time students	344	78.5%	215	83.0%	129	72.1%
Part-time students	94	21.5%	44	17.0%	50	27.9%
Freshman (number of students)	27	6.2%	6	2.3%	21	11.7%
Sophomore (number of students)	74	16.9%	23	8.9%	51	28.5%
Junior (number of students)	95	21.7%	19	7.3%	76	42.5%
Senior (number of students)	242	55.3%	211	81.5%	31	17.3%

TABLE 2**:** Grade Distribution of 438 Students Enrolled in Online Economics (Econ) and Finance (Fina) Courses During the Spring and Fall 2008 Semesters.

Class characteristic	Full Sample	**%**	Econ	**%**	Fina	**%**
Average student GPA	2.80		2.84		2.68	
Median student GPA	2.78		2.85		2.74	
Variance in student GPA	0.28		0.27		0.29	
Average grade in online class	B		B		B	
Median grade in online class	B		B		B	
Variance in grade in online class	1.57		1.61		1.51	
Number of online courses offered	10		5		5	
Average time spent online (hours per week)	2h 16m		2h 09m		2h 24m	
Standard deviation of time spent online (hours per week)	1h 24m		1h 20m		1h 26m	
Grade distribution						
F (number of students)	40	9.1%	27	10.4%	13	7.3%
D (number of students)	30	6.8%	13	5.0%	17	9.5%
C (number of students)	87	19.9%	50	19.3%	37	20.7%
B (number of students)	132	30.1%	80	30.9%	52	29.1%
A (number of students)	149	34.0%	89	34.4%	60	33.5%

TABLE 3: Definition of Variables.

GRADE	= Final grade in an online course; 4-point scale with A representing 4 and F equaling 0
TIME	= Time the student is online working on course content, in minutes per week.
GPA	= GPA of student enrolled in an online course at the beginning of the semester; 4-point scale.
AGE	= Age of student enrolled in an online course.
GEN	= 1 if student is female; 0 if male.
PHRS	= Cumulative number of credit hours student has taken prior to enrolling into the course.
MAJOR	= 1 if the online class corresponds to the student's major; 0 otherwise.
IC0 - IC6	= Dummy variables for the seven different courses and instructors. Each variable takes a value of 1 for a certain course and instructor, and 0 otherwise. IC0 is the reference category. See Table A1 in the Appendix for details.

TABLE 4: Estimates of the Ordered Logit Model for the Full Specification and the Restricted Specification.

	Full Specification			Restricted Specification		
Variable	Estimate	Std. Error	P value	Estimate	Std. Error	P value
GPA	2.246	0.225	0.000	2.267	0.224	0.000
TIME	0.009	0.001	0.000	0.009	0.001	0.000
GENDER	-0.213	0.191	0.265	-0.200	0.189	0.289
MAJOR	0.509	0.292	0.082	0.493	0.291	0.090
AGE	-0.007	0.016	0.644	-	-	-
PHRS	0.003	0.004	0.439	-	-	-
IC1	-0.948	0.292	0.001	-0.872	0.269	0.001
IC2	-0.868	0.416	0.037	-0.886	0.416	0.033
IC3	0.175	0.415	0.673	0.117	0.409	0.775
IC4	0.672	0.360	0.062	0.804	0.312	0.010
IC5	-0.884	0.393	0.024	-0.724	0.324	0.025
IC6	0.808	0.491	0.099	0.813	0.490	0.097
Sample size:	438 observations			438 observations		
Pseudo R^2:	0.1882			0.1876		

TABLE 5: Generalized Ordered Logit Coefficients for TIME.

	Coefficient	Std. Error	P value	95% Conf. Interval	
A vs. B, C, D, F	0.0039	0.0015	0.009	0.001	0.007
A and B vs. C, D, F	0.0069	0.0018	0.000	0.003	0.010
A, B, and C vs. D, F	0.0125	0.0028	0.000	0.007	0.018
A, B, C, and D vs. F	0.0265	0.0047	0.000	0.017	0.036

Notes: Sample size contains 438 observations; Pseudo R^2: 0.172

TABLE 6: Effect of One Standard Deviation (84 minutes) Change in Time Spent Online on the Probabilities of Attaining Different Letter Grades for Selected GPA Levels.

Grade	GPA = 4.0	GPA = 3.5	GPA = 3.0	GPA = 2.0
A	9.90%	17.37%	17.52%	4.12%
B	-7.77%	-11.53%	-4.53%	10.86%
C	-1.66%	-4.42%	-8.94%	2.44%
D	-0.27%	-0.81%	-2.25%	-5.67%
F	-0.20%	-0.60%	-1.80%	-11.75%

TABLE 7: Estimates of the OLS Regression Using Overall Grade as Dependent Variable (Model 1) and Grade on the Final Exam as Dependent Variable (Model 2); and Estimates of the Ordered Logit Regression Using Overall Grade as Dependent Variable (Model 3) and Grade on Final Exam as Dependent Variable (Model 4) in the Principles of Microeconomics Subsample.

	OLS Regression				Ordered Logit			
Variable	Model 1		Model 2		Model 3		Model 4	
GPA	0.1328	***	0.1000	***	2.8586	***	2.3303	***
TIME	0.0006	***	0.0004	**	0.0119	***	0.0110	***
GENDER	-0.0304		0.0012		-1.0956	**	0.0832	
MAJOR	0.0143		-0.0310		0.3503		0.0411	
Constant	0.3445	***	0.5677	***	-		-	
Sample size:	102		102		102		102	
Adjusted R^2:	0.431		0.189		0.244		0.185	

Note: ** and *** denote statistical significance at the 5% and 1% level, respectively.

TABLE 8: Estimates of Alternative Model Specifications Using OLS Regressions on the Principles of Microeconomics Subsample.

Variable	Model S1		Model S2		Model S3	
GPA	0.1328	***	0.1339	***	0.1338	***
TIME	0.0006	***	0.0007	***	-	
SESSIONS	-		-0.0001		0.0008	**
GENDER	-0.0304		-0.0304		-0.0184	
MAJOR	0.0143		0.0146		0.0113	
Constant	0.3445	***	0.3436	***	0.3705	***
Sample size:	102		102		102	
Adjusted R^2:	0.431		0.426		0.368	

Note: ** and *** denote statistical significance at the 5% and 1% level, respectively.