Time Spent Online and Student Performance in Online Business Courses: A Multinomial Logit Analysis[1]

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Abstract

This study examines the determinants of academic achievement in online business courses. As a measure of effort, we use the total amount of time each student spent in the course. We estimate a multinomial logistic model to examine the odds of attaining one grade versus another depending on time spent online, GPA, and some demographic characteristics of students. Our findings suggest that extra effort can help a student move from letter grades F, D and C to grade B, but is less helpful for the move from B to A. For the latter improvement, a high GPA matters the most.

Introduction

The determinants of academic performance are a recurrent topic in public policy debates on higher education. One largely unsettled issue concerns the impact of the most essential factors in the educational production—student's effort and study time—on academic achievement. While many would probably agree that students will not learn unless they put forth some amount of effort, our understanding of the ways study time impacts performance as measured by attaining a certain course grade is rather limited. Quantifying the effect of study time on achievement seems important from at least three perspectives: from the perspective of the administrator who is in charge of the design of effective teaching policies; from the perspective of the instructor, who creates classroom learning experiences and measures learning outcomes; and finally from the perspective of the student who seeks to balance competing personal goals.

In recent years much effort has been dedicated to understanding the factors contributing to the success of undergraduate business students. Nonis, Philhours, Syamil, and Hudson (2005) analyze survey data containing demographic, behavioral, and personality variables of 228 undergraduate students attending a medium size AACSB accredited public university. Using a hierarchical regression model they find that self-reported time per credit hour spent on academic activities outside of class explains a significant portion of the variation in the semester grade point average (GPA) for senior students, but has no impact on the cumulative GPA. Brookshire and Palocsay (2005) analyze the performance of undergraduate students in management science courses and report that overall academic achievement as measured by students' GPA has a significantly higher impact on achievement than students' mathematical skills as measured by math SAT scores.

Most of the existing literature on the topic relies on surveys in which students self-report the amount of time spent in a particular course or in a particular time frame, which is usually a semester or a year (see, e.g. Michaels and Miethe, 1989; Borg, Mason and Shapiro, 1989; Park and Kerr, 1990; Didia and Hasnat, 1998; Nofsinger and Petry, 1999; Cheo 2003; Williams and Clark 2004). The major concern associated with this approach is the accuracy and completeness of the collected data. Stinebrickner and Stinebrickner (2004) emphasize that the reporting error from retrospective survey questions is likely to be substantial. They discuss estimators that might be appropriate when reporting errors are common yet highlight the limitations of the results obtained from the analysis of such data samples.

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This study, in contrast, analyzes *actual* rather than *self-reported* data on student activities in *online* courses during the course of an entire semester. Our sample includes 532 students who were enrolled in 13 courses offered online by the College of Business at a large public university in South Texas in the spring semester of 2008. We merge detailed information on student activities in online courses (in particular the total amount of time spent online) with administrative data on demographic characteristics and academic performance prior to taking these courses. The online course tracking device we use keeps a detailed record of individual student activity with a precise measure of the time each student spends on each activity of a course.[3]

The role of effort as measured by time spent on academic activities has been the focus of much research in recent years. A major limitation of this research is the paucity of actual (i.e. not self-reported in surveys) data on student activities. Johnson, Joyce and Sen (2002) measure student effort by the number of attempts and the amount of time spent by students on computerized quizzes. Lin and Chen (2006) estimate the relationship between attendance and exam scores whereby they differentiate between cumulative class attendance and attendance of lectures. A similar approach is taken by Romer (1993), who advocates for mandatory attendance based on the results from an extensive study performed on a data sample from three schools: a medium-sized private university, a large public university, and a small liberal arts college. Rich (2006) analyzes a self-collected data sample of students who took his senior-level corporate finance class at Baylor University. He finds a positive and significant relationship between grades and several measures of effort including class attendance, arriving on time, contribution to class discussion, and attempts at homework problems. All these analyses are based on ordinary least squares (OLS) regressions.

The present study differs from this literature in its empirical strategy. We use a multinomial logistic model (MNLM) with five different categories (grades A, B, C, D, and F) rather than an OLS estimation. Thus, our methodology will be similar to the one adopted by Park and Kerr (1990) but our data would be actual rather than self-reported. This methodology enriches previous analyses in two distinct ways. First, unlike the OLS regression, the MNLM is more appropriate for discrete dependent variables such as a course grade. Spector and Mezzo (1980), among others, contain a discussion of the inadequacies of the OLS method. In particular, they discuss the assumptions underlying OLS that will be violated when the dependent variable is not continuous. Second, the MNLM renders valuable additional information that is not obtainable using OLS. An OLS coefficient provides the marginal effect of, say, one additional hour of study on the grade attained. This coefficient does not differentiate between the additional effort of a student necessary for moving from C to B and the one necessary for moving from B to A. The MNLM, in contrast, provides this additional information, and, as we will see, it is substantially more costly for a student to move from B to A rather than from C to B as far as time spent online is concerned.

The rest of the paper is organized as follows. Section 2 contains a description of our data sample and section 3 introduces the multinomial logit model. Section 4 presents the empirical results, section 5 discusses alternative model specifications, and section 6 concludes.

Data description

We obtain data on students enrolled in online business courses during the Spring 2008 semester at the College of Business of a large public university in South Texas from two sources. The first source contains the track record of student activities in the online courses. We focus only on fully online courses offered by the College of Business. Students in these courses do not necessarily meet face-to-face with the instructor throughout the semester. All the course instructors who taught these courses are fulltime tenure track or tenured professors. The university uses Blackboard (campus edition) as a Learning Management System and keeps detailed student activity data per class in Blackboard's tracking record summary. The second data source contains demographic and academic information about students obtained from the University's Office of Admissions and Records. We merge both databases and eliminate any identifier that could lead to the recognition of an individual subject in order to ensure anonymity.

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[3] This university uses Blackboard (Campus edition) as a Learning Management System for online courses. This software allows instructors and students to meet in a closed area online to participate in coursework. Blackboard's activity tracking feature keeps a record of various student activities, including log in and log out time of each session, number of sessions, breakdown of the time spent in various learning modules, participation in discussion boards (including messages posted and messages read), number of emails sent and received for each student, etc. For the period of the Spring semester of 2008, the vast majority of the students who took an online class (89.1%) used a high-speed internet connection such as cable-modem, T1 or broadband to gain access to the courses. About 2.1% used a dial up connection, and the remaining 8.8% used other types of connections (figures retrieved from Google Analytics for all users accessing the university's online learning web site during the Spring semester of 2008).

From the initial sample of 563 students we remove those that voluntarily dropped the course before the 12th day of classes. The final sample consists of 532 students who enrolled and completed one of 13 online courses offered by the four departments in the College of Business: Economics and Finance (Introduction to Economics, two sections of Principles of Microeconomics I, Managerial Finance, and International Finance); Accounting and Business Law (Professional Ethics, and Business Law I); Computer Information Systems (Management Information Systems); and Management, Marketing and International Business (Communication Policy, Principles of Marketing, International Marketing, and two sections of International Business).

Table 1 shows that, on average, almost 41 students were enrolled per online class. The average student age was 25 years and the median age was 23 years. There were 215 (40.4%) male students and 317 (59.6%) female students. Given that our sample comes from a minority serving institution, more than 85% of the students were of Hispanic origin. There were 431 full-time and 101 part-time students enrolled. The majority of students described themselves as Senior (56.2%) followed by Junior (28.9%).

Table 1: Descriptive statistics of 532 students enrolled in an online business course during the Spring 2008 semester

Class characteristic	#	%
Average class size (number of students)	40.92	
Average student age (in years)	25.07	
Median student age (in years)	23.00	
Male (number of students)	215	40.4%
Female (number of students)	317	59.6%
Hispanic (number of students)	454	85.3%
Non Hispanic (number of students)	78	14.7%
Full-time students	431	
Part-time students	101	
Freshman (number of students)	12	2.3%
Sophomore (number of students)	37	7.0%
Junior (number of students)	154	28.9%
Senior (number of students)	299	56.2%
Graduate (number of students)	30	5.6%
Average student GPA	2.86	
Median student GPA	2.84	
Variance in student GPA	0.25	
Grade distribution		
F (number of students)	40	7.5%
D (number of students)	48	9.0%
C (number of students)	97	18.2%
B (number of students)	175	32.9%
A (number of students)	172	32.3%

The average student grade point average (GPA) prior to taking the online class was 2.86 while the average and the median grade obtained per enrolled student was a B, with a variance of 1.48. At the end of the semester, the number of students who received grades A, B, C, D, and F were 172 (32.3%), 175 (32.9%), 97 (18.2%), 48 (9%), and 40 (7.5%), respectively. Graph 1 shows the final grade distribution depending on the time students spent online in the class. In some courses, the average time spent per student was significantly higher than in others. In order to make time comparable across classes, in each course we standardize the time students spent online. From the actual time (in minutes) for each student we subtract the average time for all students in this course and divide the result by the standard deviation of time spent in the course. Standardized time is thus normally distributed with a mean of zero and a standard deviation of one. Blackboard automatically logs students off from courses after 20 minutes of inactivity. Therefore, we believe that our measurement captures quite accurately the actual time students spent online. Graph 1 illustrates that students who spent the least amount of time online (those included in the lowest quintile) earned the largest proportion of failing grades (F). In contrast, the students who spent the most time online received the smallest proportion of F grades. This group also received the largest proportion of A grades. Generally, Graph 1 suggests a positive relationship between time spent online and final grade.

Graph 1 - Grade Distribution by Time Spent Online
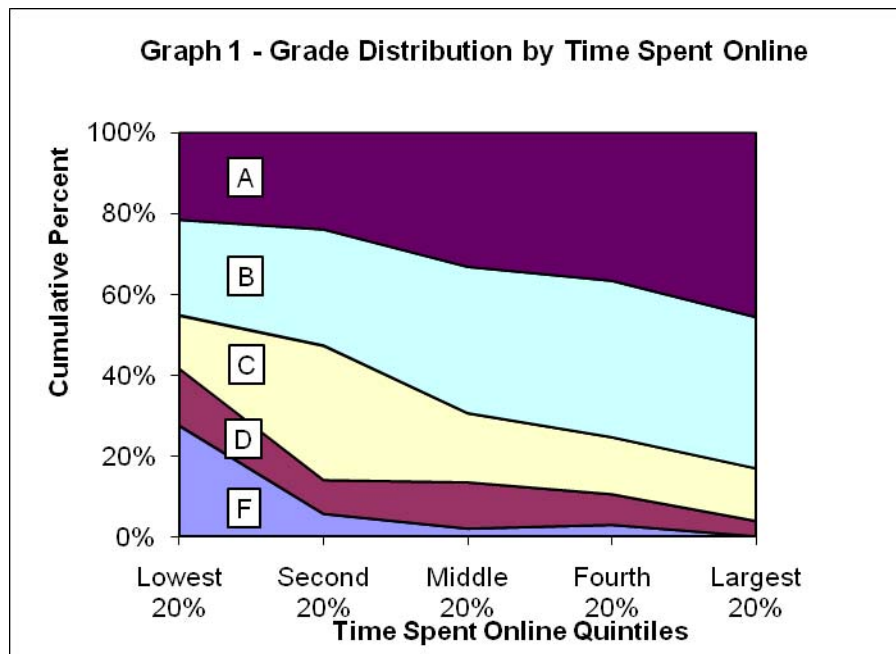
Multinomial logit model (MNLM)

We use a multinomial logistic regression to analyze how the odds of receiving a specific grade versus another depend on the time the student spent online and the student's GPA prior to taking the course. These two variables, which are broadly interpreted as student *effort* (or preparation) and *ability* (or intelligence), are major inputs in the learning production function. We also control for age, gender, major, and number of credit hours taken prior to enrolling in the course. Thus, our model has six explanatory variables defined as follows:

GRADE = the letter grade (A, B, C, D, F) the student received in the course, with A = 4, B = 3, C = 2, D=1, and F = 0

GPA = the grade point average (scale 0-4.0) of the student at the beginning of the semester.

TIME = the actual time the student spent online working on course content, standardized per class.

AGE = age of the student at the time he/she took the course.

GEN   = 1 if student is female; 0 if male.

MAJOR = 1 if the online class is offered by the same department of the student's declared major; and 0 otherwise.

PHRS = the total credit hours the student had accumulated prior to enrolling into the course.

As a base category (or comparison group) we choose the category with the largest number of observations (see Long 2006, p. 231). In our case the most frequently assigned grade is the letter grade B. More specifically, the MNLM specifies the logarithm of the odds of grade $i = A, C, D, F$ versus grade B as a linear function of the explanatory variables. Thus, the MNLM is specified by four equations:

$$\frac{\ln(\Pr(i))}{\Pr(B)} = \alpha_{iB} + \beta_{2,iB} GPA + \beta_{2,iB} TIME + \beta_{3,iB} AGE + \beta_{4,iB} GEN + \beta_{5,iB} MAJOR + \beta_{6,iB} PHRS$$

where $i = A, C, D, F$. These four equations can be solved to calculate the probabilities for each grade i as a function of the six explanatory variables (and the regression estimates for the coefficients):

$$\Pr(i) = \frac{\exp(Z\beta_{iB})}{\sum_{j=A,B,C,D,F} \exp(Z\beta_{jB})}$$

where $Z = (GPA, TIME, AGE, GEN, MAJOR, PHRS)$ is the vector of explanatory variables and $\beta_{jB} = (\beta_{1,jB}, \beta_{2,jB}, \ldots, \beta_{6,jB})$ is the vector of coefficients.[4] The coefficients are obtained using maximum likelihood estimation, which ensures consistency of the estimates when explanatory variables are categorical (see e.g. Park and Kerr, 1990). The estimation is based on the *independence of irrelevant alternatives* assumption, which implies that the odds of one grade versus another do not depend on the availability of other grades. We confirm the validity of this assumption for our data sample by performing a Small-Hsiao test (see Long 2006, p. 245). The results of this test are reported in Table A.3 in the Appendix. A direct check of the correlation coefficients (see Table A1 in the Appendix) and some preliminary OLS estimations also reveals that no multicollinearity exists between explanatory variables in our data sample.

Empirical results

Our major findings are presented in Table 2, which contains the multinomial logit coefficients for the logarithms of the odds of all grades versus the base category B, followed by the z-values in parenthesis, and the marginal effects of each explanatory variable on the probability of receiving a particular grade. The marginal effects are calculated by the formula

$$\frac{\partial \Pr(i)}{\partial x_k} = \Pr(i) \left[\beta_{k,iB} - \sum_{j=A,B,C,D,F} \beta_{k,jB} \Pr(i) \right]$$

where x_k, $k = 1, 2, \ldots, 6$ denote the explanatory variables GPA, TIME, AGE, GEN, MAJOR, and PHRS, respectively. The partial derivative is evaluated at the sample mean of each regressor. In contrast to the *multinomial logit coefficients*, which specify the impact of each explanatory variable on the log-odds ratio of one grade versus another, the *marginal effects* determine the impact of a small change in each explanatory variable directly on the

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[4] The coefficients α_{iB} are normalized to zero to ensure the identification of the coefficients in the β_{iB} vectors (see e.g. Greene, p. 721).

probability of receiving a particular grade. As is evident from Table 2, the marginal effect of TIME is positive for grades A and B, and negative for grades C, D and F. The marginal effect of GPA is positive only for grade A and negative for all other grades.

Table 2: Multinomial Logit Estimates and Marginal Effects of the Time Spent Online on Class Grade

|	Grade B	Grade A	Grade C	Grade D	Grade F
Constant	–	-5.803***	4.172***	8.125***	3.872**
		(-5.38)	(3.52)	(4.96)	(2.12)
GPA		1.558***	-1.243***	-3.029***	-2.155***
		(5.79)	(-3.7)	(-5.65)	(-3.89)
	-0.022	0.464	-0.266	-0.146	-0.031
TIME		0.061	-0.362**	-0.741***	-2.751***
		(0.52)	(-2.34)	(-3.11)	(-6.21)
	0.055	0.058	-0.048	-0.029	-0.036
AGE		0.019	-0.020	-0.027	-0.000
		(0.97)	(-0.81)	(-0.79)	(0.00)
	-1.714E-04	0.006	-0.004	-0.001	-0.000
GEN		-0.022	-0.226	0.284	-0.162
		(-0.09)	(-0.85)	(0.77)	(-0.39)
	0.018	0.006	-0.038	0.015	-0.002
MAJOR		-0.068	-0.166	-0.598	0.214
		(-0.28)	(-0.58)	(-1.41)	(0.49)
	0.034	0.003	-0.018	-0.023	0.004
PHRS		0.006	-0.006	-0.009	-0.011
		(1.33)	(-1.26)	(-1.34)	(-1.31)
	4.150E-05	0.002	-0.001	-0.000	-0.000

Log likelihood: -630.46

Pseudo R^2: .181

N = 532

Notes: The logit coefficients are followed by the *z*-values (in parenthesis) and the marginal effects evaluated at the sample means. The reference category is Grade B. ** and *** indicate significance at the 5% and 1% level respectively, using two-tailed tests.

The GPA coefficients for the logarithm of the odds for all grades versus B are significant at the 1% level and have the expected signs since letter grade B is the reference category. The TIME coefficients are also significant at the 1% level except for the coefficients of the odds A vs. B (non-significant), and the odds of C vs. B (significant at the 5% level). For instance, a unit increase in the time spent online increases the log odds of getting an A vs. B by 0.061 and decreases the odds of getting a C vs. B by 0.362. Note also that the coefficients for TIME monotonically increase moving from F upward which is consistent with diminishing marginal returns to effort. The coefficients for all other variables are insignificant. This may suggest that there may be an identification problem inherent to our model specification. The goodness of fit of our logistic regression as measured by the Pseudo R^2 is 0.181, which may imply the possibility of other variables having an impact on the log-odds of one grade versus another.

Graph 2: Odds-ratio plot of grade relative to base category B

Factor Change Scale Relative to Category B
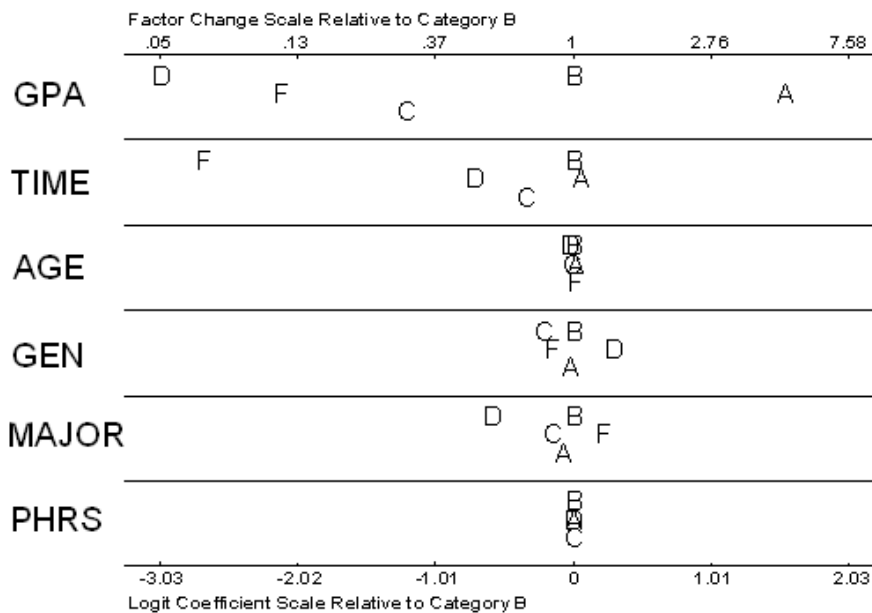
These results are also visualized in Graph 2. Each row in this graph presents the effect of an independent variable on the log odds ratios (scale is above the graph) of each grade versus grade B. If a letter grade is positioned to the right of another letter grade, then an increase of the explanatory variable makes the odds for the outcome to the right more likely (Long 2006). In fact, the distance between each pair of letters indicates the magnitude of the effect because it corresponds to the value of the logit coefficients reported in Table 2. As is evident, the impact of GPA on grade is almost evenly spaced across grades, with letter grade A to the very right, followed by B and C. The spaces A – B and B – C seem equally large and a little larger than the spaces between the other grades, indicating that ability plays an important role in determining a student's chance of receiving grades A or B. The ordering of D and F is somewhat surprising because it indicates that a high GPA makes it more likely for a student to receive an F instead of a D. One possible explanation for this observation is that students with a good GPA prefer to fail and retake a class in which they see that they will obtain the lowest passing grade.

Two issues are worth emphasizing when it comes to the effect of TIME. First, the failing grade (F) lies much further to the left of all other grades. This indicates that a very small increase in student time spent online will substantially reduce a student's odds of failing a course. Second, the grades A and B are clustered together (although the ordering is as expected). This signals that the odds of getting an A versus B cannot be improved upon substantially by increased amount of time spent online. Ability seems much more important than effort for an A grade in the courses. The letter grades for all other variables are clustered together, which indicates that the impact of these variables is minimal.

Table 3: Odds of getting one grade versus the next best grade

	A vs B	B vs C	C vs D	D vs F
GPA	1.557***	1.242***	1.785***	-0.873
	(0.269)	(0.335)	(0.541)	(0.648)
TIME	0.061	0.361**	0.379	2.009***
	(0.117)	(0.154)	(0.246)	(0.461)

Notes: the coefficient values are followed by standard errors in parenthesis. ** and *** indicate significance at the 5% and 1% level respectively, using two-tailed tests.

A common student question concerns the amount of effort necessary for a student to move to the next best grade, and Table 3 provides a perspective on this issue. It contains the coefficients for GPA and TIME for the odds of moving to the next best grade. As is evident, previous track record of high performance as measured by student's GPA will improve the odds of receiving a higher grade. At the conventional significance levels, the odds of getting one grade versus the next best grade are all statistically significant with the exception of the last column which reports the odds of moving from F to D. For this move, effort is much more crucial. Effort will also help a student move from C to B (the coefficient is significant at the 5% level).

The estimated model can predict the expected achievement of a student with certain characteristics based on the effort of the student as measured by the time spent online. Table 4 presents the probabilities for receiving various grades of a 23-year-old female student taking a course in the department of her major with a current GPA of 3.0, and 18 credit hours already taken. The first row presents the probabilities for obtaining various grades if she spends a time equal to the average time (AVG) that students spend in class, and the second row reports the probabilities in case she increases her time spent online to one standard deviation above the average (AVG+1SD).

Table 4: Impact of time on the chances of receiving a particular grade for a student with certain characteristics.

	A	B	C	D	F
AVG	21.95%	43.62%	26.00%	5.60%	2.83%
AVG+1SD	26.53%	49.63%	20.60%	3.04%	2.10%

Table 4 reveals that, as a result of the extra effort, the chance of this student of receiving an A increases by 4.48% and the chance of receiving a B by 6.1%. The chances of receiving each one of the other grades C, D, and F decreases.

The MNLM assumes that the logarithms of the odds of one grade versus another are linear in the independent variables. To test the validity of this assumption we also considered two alternative specifications of the model. To check for nonlinear relationships regarding time spent online we added a squared term of this variable; and to test for possible interaction between the ability of the student (as measured by the GPA of the student) and effort (as measured by time spent online) we considered a regression with an interaction term of these two variables. The coefficients for both the interaction term and the squared term are not significant, which lends support for the final

specification adopted. As an alternative, we also analyzed subsamples of the data. We created the following subsamples: economics and finance and computer information systems (EF+CIS); computer information systems and marketing, management and international business (CIS+MMIB); and marketing, management and international business and economics and finance (MMIB+EF).[5] The results for the subsamples are found to be qualitatively the same as the ones for the entire database.

Discussion

This study focuses on the role of time spent online on academic performance. While we believe the total amount of time spent on a course is a good measure of student effort, it might be interesting to further explore how this time is allocated to various activities. Alternative measures of effort in our online courses can be number of sessions (i.e., number of times a student logged into the course), number of emails, number of messages posted on discussion boards, etc. An analysis of those measures might shed further light on the ways students learn, and which activities, on average, contribute to performance.

Our study is based on data collected from online courses in one large public university, but as data from online courses become available it will be important to expand the current study to data from courses in other institutions. It will also be interesting to compare the effect of time between online and traditional courses yet the progress in this direction will clearly depend on the availability of reliable data from traditional courses.

Sometimes students are content getting a particular grade and seek to dedicate the minimum effort possible which will guarantee that they will attain this grade. Thus, the factors which motivate students to expend effort might be different depending on whether students are grade satisfiers or grade maximizers. Our dataset is static in nature and does not allow us to differentiate between the two groups of students or somehow classify students depending on their motives to spend time studying. To this end we need to have detailed information on student performance throughout the semester.[6]

Conclusion

The literature on the impact of student effort on performance naturally divides in two categories based on the data used and the empirical results. The analyses relying on *self-reported* measures of student effort in general tend to find a weaker or no relationship between effort and performance, while the analyses using *real* measures of effort find a much stronger link between effort and educational outcomes. For instance, Stinebrickner and Stinebrickner (2003) find that working students consistently attain a lower GPA compared to full-time students, and Dávila and Mora (2004) find that students with entrepreneurial parents have a lower achievement in mathematics and reading compared to students coming from salaried households.

This paper uses data on the real time students spent in online classes to examine the link between the time put forth in a particular online class and the grade attained in this class. We find a positive and significant relationship between study time and grade; yet, our analysis also uncovers the limits of what a student can achieve by putting forth extra effort in a particular course. While study time is quite helpful for a student to move away from the grades F, D and C, and attain a B instead, effort, although beneficial, has only a statistically insignificant contribution for the improvement from B to A. For this improvement, overall GPA is the more important determinant.

The number of institutions offering online courses has grown steadily in the last several years and student enrollment in online courses has also risen significantly. Therefore, understanding the determinants of academic success in online classes has become increasingly important to administrators, professors, and students. Our findings suggest that activities encouraging students to spend more time online will result in a higher educational achievement. Students should know that educational success will be much more likely when time and effort is put forth from the day they come to the university.

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[5] We would like to thank an anonymous referee for this suggestion.

[6] We thank an anonymous reviewer for pointing out this issue.

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Appendix

Table A.1: Pairwise correlation coefficients

	GRADE	GPA	TIME	AGE	GEN	MAJOR	PHRS
GRADE	1						
GPA	0.519	1					
TIME	0.329	0.171	1				
AGE	0.081	-0.009	0.193	1			
GEN	0.097	0.104	0.113	0.074	1		
MAJOR	0.106	0.189	-0.052	-0.037	-0.001	1	
PHRS	0.229	0.196	0.071	0.139	0.029	0.257	1

Table A.2: Likelihood-ratio tests for independent variables
Ho: All coefficients associated with given variables are 0

	Chi Square	df	P>Chi Sq.
GPA	141.002	4	0.000
TIME	71.944	4	0.000
AGE	2.973	4	0.562
GEN	2.159	4	0.706
MAJOR	3.108	4	0.540
PHRS	7.369	4	0.118

Table A.3: Small-Hsiao test of the independence of irrelevant alternatives.
Ho: Odds (Outcome-J vs Outcome-K) are independent of other alternatives.

Omitted	lnL(full)	lnL(omit)	Chi Sq.	df	P>Chi Sq.	Evidence
Grade A	-180.974	-172.192	17.563	21	0.676	for Ho
Grade C	-201.379	-194.789	13.180	21	0.902	for Ho
Grade D	-244.244	-235.584	17.320	21	0.692	for Ho
Grade F	-271.994	-264.723	14.541	21	0.845	for Ho

Table A.4: Predicted probabilities

Variable	Observations	Mean	Std. Dev.	Min	Max
GPA	532	2.859	0.503	1.605	4.000
GRADE	532	2.735	1.215	0.000	4.000
Grade A	532	0.321	0.222	0.002	0.890
Grade B	532	0.329	0.107	0.025	0.590
Grade C	532	0.183	0.099	0.001	0.438
Grade D	532	0.091	0.106	0.000	0.612
Grade F	532	0.076	0.131	0.000	0.776