ECONOMETRIC STUDY OF TIME USE AND SCORES IN ONLINE MBA STATISTICS CLASS: A GENDER ANALYSIS

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ABSTRACT

Improved Student learning is the ultimate goal of educators and is generally measured in terms of scores earned in the course. Students themselves must also dedicate adequate hours to the course. The present study provides evidence that a student's final grade is closely linked to the hours spent in the course, especially with regard to online statistic courses. This study uses actual recorded online time use of students instead of self-reported surveys used in most studies in the relevant literature. Moreover, the models use actual scores instead of the letter grades which hide a lot of information by converting the ratio scale variable to discrete ordinal variable. As a result, this study could use Constant elasticity and Decreasing Elasticity Mixed Dummy Multiple Regression models assuming that online time use is an objectively measurable good indicator of overall effort by students in online classes. The evidences suggest that there is a significant reward for additional effort, especially at the lower levels of times use and scores. The Constant Elasticity model predicts a 4.3% improvement in existing score for additional 10% increase in online time use for male students. For female students the improvement is expected to be only about 2.5% in existing score. The gender difference is highly significant statistically in the Constant Elasticity model. The decreasing Elasticity model is not only theoretically more appealing but also most successful in explaining variations in the scores, although the gender difference gets dampened and loses some of its statistical significance in this model. According to this model, a 10% increase in online time use for male students with minimal online time use (about 9.2 hours over the semester), is expected to improve the existing score by 3.8% of existing score. For a similar female student the predicted improvement is 3.1% of existing score. As the level of time use increases to the mean level (76.4 hours over the semester), the elasticity for male students drops to 0.05 indicating that a 10% increase in time use would be expected to improve existing score only by 0.5%. The gender difference at higher levels of time use becomes very small. The results of this study are particularly significant for students with low online time use. Instructors should encourage such students to significantly increase their effort as it promises much larger reward at the lower end of time use. Although few students can and have achieved high scores despite their low online time use, it is clear from the data that very low online time use is a good predictor of low scores with few exceptions. This research can be extended by including other objectively measurable attributes and also covering other subjects.

INTRODUCTION

Online MBA is relatively a recent but exponentially expanding phenomenon. The factors contributing to students' success in this online paradigm is topic of recurrent interest for Higher Education Administrators, Academicians, Communities and Students. There have been several studies in the relevant literature which attempt to identify and quantify the relationships of various factors with students' academic performance/achievement. But there is a dearth of econometric study of the impact of the single most important key factor, namely, students' effort measured by online time use, on students' performance with a gender perspective, especially for graduate students. In the literature pertaining to student participation and effort, most studies have concentrated on the simple measure of attendance. Many studies have found that class attendance positively affects performance across various subjects. For example, Devadoss and Foltz (1996) for Agricultural Economics; Schmidt (1983), Park and Kerr (1990), Romer (1993), Durden and Ellis (1995), Ellis and Durden (1998) and Cohn and Johnson (2006) for Economics; Chan et al. (1997) and Johnson et al. (2002) for Finance; Gunn (1993) and Launius (1997) for Psychology; Day (1994) for Sociology; Gump (2005) for General Education; Ledman and Kamuche (2002) for Statistics; Rodgers (2001 and 2002) for Business; Biology Gatherer and Manning (1998) for Biology; and Nyamapfene (2010) for Electronic Engineering. In contrast some studies, such as Buckles and McMahon (1971) and Douglas and Sulock (1994) found no significant contribution of class attendance on performance.

These studies provide evidence of importance of attendance for students in conventional face-to-face courses. However, the question for online and distance courses, where there is often no requirement to attend at a particular place or at a particular time is different. Since class attendance is not relevant some other measure has to be used. In online courses almost all of the interaction is through online tools such as Virtual Office Forum, Students' Forum, Discussion Board, emails to the Instructor and to peers, downloading materials posted by the Instructor, Class live sessions, etc. Participation can be defined by activities such as logging in to symmetric class sessions, participation in discussion boards and forums, online interaction with peers and Instructor, and downloading and reading class materials. There have been relatively few studies on online courses with respect to students' efforts and their performance.

This is what we propose to do in this study. The present study differs from the prevalent literature in its empirical strategy and information content of the data. We use Multiple Regression with mixed Dummy models for Gender with a data consisting of the actual scores instead of data classified into letter grades. The actual score is a ratio scale quantitative variable while letter grade is an ordinal scale discrete variable. The information content is significantly different. For example, a score of 800 is treated equally as a score of 899 (letter grade B). Obviously, the measurement of marginal impact will not only be dramatically blurred but also distorted in a very nonlinear and asymmetric way when scores are converted into letter grades. For example, a change of score from 800 to 895 will not be noticed while a much smaller change

from 895 to 900 will be recorded as change of letter grade from "B" to "A". Consequently, observations with scores marginally below some letter grade will have relatively much larger influence on positive effects; those with scores marginally above some letter grade will have much larger influence on negative effects; and those with scores in the middle will have much weaker influence either way. Thus, all observations will not be treated equally as assumed by most statistical models used in this case. Clearly, the information extracted afterwards will have severe distortions whatsoever elegant (and high sounding) statistical model may a researcher apply. Even a subsequent conversion of letter grades to a quantitative variable like GPA does not bring back the information already lost and repair the asymmetric problem mentioned above. Moreover, the set of econometric tools which can be applied to ordinal dependent variable instead of quantitative also becomes quite restricted with several limitations. Ordinary Multiple Regressions become inappropriate and models such as Multinomial Logit have to be resorted to.

Therefore, the present study makes an important contribution by using quantitative measurement of students' performance, using Multiple Regressions and Mixed Dummy (Slope and Intercept) for Gender. It is often useful to employ a methodology different from those in prior studies to provide a fresh perspective and confirmation or contradiction of previous findings.

Another important deviation of the present study from the prevalent literature is in the collection of data. Many studies rely on the data collected from students' surveys where the students do self-reporting. Such data clearly involve large measurement errors whose size and nature are not easy to estimate. This approach clearly lacks desired 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.

Our data consist of actually recorded time use and scores in the e-college system used by online courses of Texas A & M University-Commerce, a medium size public University with AACSB accredited online MBA. Our sample includes 308 students who completed graduate level Statistics course in the MBA program from Fall of 2009 to Fall of 2011. The e-college system keeps a detailed record of individual student activity with a precise measure of the time (in minutes) each student spends on each activity of a course. The rest of the paper is organized as follows. Section 2 contains a brief review of the relevant literature. Section 3 contains a description of our data sample and econometric methodology. Section 4 presents the empirical results and section 5 concludes.

REVIEW OF SELECTED LITERATURE

There have been several studies on class attendance and students' performance in traditional face-to-face classes. Schmidt (1983) reported that time spent attending lectures in a

Page 62

macroeconomic principles course contributed positively to performance. Park and Kerr (1990) found that attendance was a determinant of student performance in a money and banking course, although it was not as important as a student's GPA and percentile rank on a college entrance exam. Romer (1993) found that attendance did contribute significantly to the academic performance of students in a large intermediate macroeconomics course. The author admits the major problem with the study because attendance was not taken every day, thus involving a statistical measurement error. Devadoss and Foltz (1995) found, for a sample of students enrolled in agricultural economics and agribusiness courses, that the more classes attended, the better the students' grades. Durden and Ellis (1995) found that student absences had a significant, negative effect on student performance in the principles of economics course. They find a nonlinear relationship inferring that a few absences do not impact grades, but more than four were found to negatively impact grades.

Ellis, et al. (1998) use data collected by surveying students at Appalachian State University at the end of the semester in several sections of the principles of economics course (both micro and macro). A questionnaire was administered over five semesters: Spring and Fall 1993, Spring and Fall 1994, and Spring 1995. The data on absences were estimated number of classes missed during the semester as reported by the students themselves. The observations on student grades were simply the percentage of possible course points earned by the student for the semester. This study treats student performance as a dichotomous variable considering the student as either having done well or having done poorly in the course. The logit analysis employed in this study showed that the probability of a student earning a grade of A or B in Principles of Economics declines as the number of missed classes increases, and the probability of a student earning a D or F increases as classes missed increases. Other factors that positively affect the chances of earning a good grade are the student's GPA, taking calculus and SAT scores. Other negative influences include membership in a fraternity or sorority and the number of credit hours carried during the semester. This study also finds that while females are just as likely as males to do well in principles, they are more likely than males to do poorly for virtually all levels of class attendance, other things being held constant.

Burrus et al. (2001) find that hours of study and student perception concerning the usefulness of homework assignments in preparing for exams increases a student's performance on homework assignments. Ninety-eight students in Principles of Macroeconomics, a prerequisite for all business majors, are surveyed about their perception of homework effectiveness during the Spring and Fall semesters of 1999.2 Students provide categorical information on their GPA's (*GPA*), hours spent studying course material (*HSD*), the perceived usefulness (*USE*) of the homework in exam-preparation and the time (*TME*) given to complete the assignments.3 Students complete the surveys during the final class meeting. Marburger (2001) uses detailed information on 60 students enrolled in a section of microeconomics principles over a single semester to investigate the impact of attendance on particular days on exam grades. In his study, lecture material is matched with respective multiple choices questions

Journal of Economics and Economic Education Research, Volume 13, Number 3, 2012

to determine if a student is more likely to miss a question covered on the day of an absence. In his study, lecture material is matched with respective multiple choices questions to determine if a student is more likely to miss a question covered on the day of an absence. Ledman and Kamuche (2002) using correlation analysis and tests of hypothesis show that student test performance is better when class attendance is better and that students with better attendance demonstrate more knowledge of the course material. Johnson et al. (2002) study the relation between performance and effort by students in an introductory financial management course. Instead of relying on self-reported data, this study used objectively measured data on effort by the number of attempts made and the amount of time spent by students on repeatable computerized quizzes. The authors find that effort positively influences student performance and encourage educators to motivate students to exert effort in their education. Stinebrickner and Stinebrickner (2004) study the relationship between educational outcomes and students' study time and effort using unique new data from the Berea Panel Study.

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. The study by Lin and Chen (2006) considers the effect of cumulative class attendance while estimating the relationship between class attendance and students' exam performance, using an individual-level data. They find that, cumulative attendance produces a positive and significant impact on students' exam performance. Attending lectures corresponds to a 4% improvement in exam performance, and the marginal impact of cumulative attendance on exam performance is also close to 4%. However, the impact of attendance on exam performance is reduced about 0.4% after controlling for the cumulative attendance effect. Cohn and Johnson (2006) use a sample of 347 students, enrolled in principles of economics classes during the period 1997-2001 to examine the relation between class attendance and student performance on examinations. Marburger (2006) investigates the impact of enforcing an attendance policy on absenteeism and student performance and concludes that an enforced mandatory attendance policy significantly reduces absenteeism and improves exam performance. Stinebrickner and Stinebrickner (2008) examine the causal effect of studying on grade performance using an Instrumental Variable estimator using longitudinal data and suggest that human capital accumulation is far from predetermined at the time of college entrance.

More recently, Crede et al. (2010) find class attendance as a better predictor of college grades than any other known predictor of college grades—including SAT scores, HSGPA, studying skills, and the amount of time spent studying. They conclude that the relationship is so strong as to suggest that dramatic improvements in average grades (and failure rates) could be achieved by efforts to increase class attendance rates among college students. Nyamapfene (2010) studies the impact of class attendance on academic performance in a second year Electronics Engineering course module with online notes and no mandatory class attendance policy. The study shows that class attendance is highly correlated to academic performance,

despite the availability of online class notes. In addition, there is significant correlation between class attendance and non-class contact with the lecturer and between student performance in the first year of university study and current academic performance and class attendance. However, there is no correlation between pre-university academic performance and current class attendance and academic performance. The study finds no gender bias in either class attendance or academic performance. Lastly, the study finds that a student's choice of degree program has no impact on class attendance and academic performance in this particular course module.

The literature on the relation between students' time spent and performance is relatively new and smaller, and most studies again relay on self reported surveys. Nonis et al. (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. George et al.(2008) use a sample of 231 students attending a private liberal arts university in central Alberta, Canada, who completed a 5-day time diary and a 71-item questionnaire assessing the influence of personal, cognitive, and attitudinal factors on success. The authors find that the greatest predictors of GPA were time-management skills, intelligence, time spent studying, computer ownership, less time spent in passive leisure, and a healthy diet.

Brint et al. (2010) find that there is a surprisingly modest relationship between UC GPA and reported hours studying reflecting differences in academic requirements and perhaps grading practices across disciplines as well as differences in individual effort required to obtain a given level of performance. On the other hand, they find that high school GPA is a good predictor of time spent studying. Students with stronger high school GPAs studied more at UC than those who had lower high school GPA. Brint and Cantwell (2010) use survey of about 6000 responses to the 2006 University of California Undergraduate Experience Survey (UCCUES). Controlling for students' socio-demographic backgrounds, previous academic achievements, and social psychological stressors, they find that study time is strongly connected to both academic conscientiousness and higher grade point averages. Uses of time that connect students to campus life showed relatively weak and inconsistent effects. This study suggests stronger focus on academic study time as the central key to positive academic outcomes, and a renewed focus on off-campus work as a major obstacle to positive academic outcomes.

In contrast to the large and growing literature related to face-to-face education there have been relatively few studies on the relationship between students' participation and performance in distance learning classes, especially at the graduate level. Cheung and Kan (2002) reported on students enrolled in a business course at the Open University of Hong Kong; they found a relationship between tutorial attendance and performance in a hybrid course. Riffell and Sibley (2005) evaluated the effectiveness of the online portion of a hybrid course in an introductory environmental biology course for non-science majors and found no relationship between lecture attendance and post-test scores. Picciano (2002) studied a totally asynchronous online graduate education administration course, dividing the students into three groups by level of participation. He found no difference in exam performance, but the high participation group (measured by substantial discussion board posts) scored significantly better on the written assignments.

Douglas and Alemanne (2007) present data comparing measures of student effort with student success on an online course. The course which is part of an online Masters program in Library and Information Science ran in the spring semester of 2007. Data was collected from 30 of the 32 students on the course. Participation was measured by counting discussion posts, class utterances, email contacts and course web site clicks. The authors conclude that class participation, no matter how crudely measured, is an important factor in academic success. However this study suffers from the limitation of the small sample size and the accuracy of the measurement of participation. For example, the students could be clicking just to improve their click count and overall grade which was partially based on such participation. Damianov et al. (2009) examine the determinants of academic achievement in online business courses. As a measure of effort, this study uses the total amount of time each student spent in the course. This study estimates 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. This study finds 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.

DATA AND METHODOLOGY

The present study is based on the recorded online time use and score of 308 MBA students in online graduate Statistics classes taught by the same Instructor at Texas A & M University- Commerce, a midsize public Institution with AACSB accredited online MBA.

This course is a core course with application across other courses and general observation suggests that achievement in this course is highly correlated with overall achievement in the program. The e-college system keeps a detailed record of individual student activity with a precise measure of the time (in minutes) each student spends on each activity of a course. The observations were classified by gender based on names and utmost care was taken for accuracy. After gender classification the names were removed to make the data completely without any identifier. The variables used in this study are Online Time Use in minutes denoted by "Tm", actual scores out of the total 1000 denoted by "Sc", and Gender denoted by "Ge". The value assigned is 0 for Male and 1 for female. Thus Gender is a Dummy variable with Male as the base case. There were 166 male and 142 female students in the sample of 308. A basic assumption underlying this study is that online time use is a good objectively measurable indicator of overall effort by students in online classes. There may be some exceptions, but these two seem to be highly correlated in general.

We use three types of Mixed Dummy Multiple regression models:	
Type1: Linear Multiple Regression	
$\mathbf{s} = \mathbf{b}_0 + \mathbf{b}_1 \mathbf{T}\mathbf{m} + \mathbf{b}_2 \mathbf{G}\mathbf{e}^* \mathbf{T}\mathbf{m} + \mathbf{b}_3 \mathbf{G}\mathbf{e}$	(1)
Type2: Constant Elasticity Double Log Multiple Regression	
$log(3c) = b_0 + b_1 log(Tm) + b_2 Ge*log(Tm) + b_3 Ge$	(2)
Type3: Decreasing Elasticity Linear-Log Multiple Regression	
$\mathbf{s} = \mathbf{b}_0 + \mathbf{b}_1 \log(\mathrm{Tm}) + \mathbf{b}_2 \mathrm{Ge*} \log(\mathrm{Tm}) + \mathbf{b}_3 \mathrm{Ge}$	(3)

The discussion about the properties of the different functional forms and the interpretations of marginal effects and elasticity can be found in any standard Econometrics book, such as Asteriou and Hall (2007, pages 161-65). The slope coefficient b_1 of the first model provides the estimated marginal impact of one unit change in time use (in minutes) on score for male students (out of 1000), while $b_1 + b_2$ provides the marginal impact of one unit change in time use on score for female students. The constant term b_0 is the estimated intercept for male students. In other words, it is the expected score (out of 1000) when online time use is zero (or nearly zero for practical purposes) for male students. On the other hand, $b_0 + b_3$ is the estimated intercept corresponding to female students.

The second model uses score and time in their (natural) log forms. This model measures elasticity (unit free) instead of marginal impact. Here b_1 measures the elasticity of scores with respect to time use for male students, that is, the percentage change is score as a result of percentage change in time use. Similarly, $b_1 + b_2$ measures the same for female students. The anti-log of the constant term is simply the scale factor. Since the scatter plot of score and time use showed somewhat nonlinear relation we tried the log-linear model along with linear model. We compare various aspects of these two models including overall explanatory power, significance of coefficients and various selection criteria. We also report several econometric tests.

Theoretically, the more appealing model is the one with variable elasticity. Here the elasticity is equal to b_1/Sc and the marginal effect is b_1/Tm . The elasticity and marginal effect decline as the levels of score and time use increase. This makes sense if we expect it to be more challenging to improve the score with effort only as the level of score increases. There is a general perception that it is harder to jump from B to A than from C to B on the basis of effort only, as also confirmed by the Multinomial Logit model findings of Damianov et al. (2009). Thus, we are also able to show that you don't need to resort to Multinomial Logit model, as perhaps claimed by Damianov et al. (2009), for estimating such asymmetric effects of efforts on achievement.

One can also argue that the variation in elasticity could be just the reverse, considering the fact that it is generally harder to earn the first million (or billion) than to earn the next million (or billion): a self reinforcing process as the student does better and better with more and more efforts. To check this, a fourth model with log of Score but Time use in original form was tried. but the results were relatively poor. All estimations and tests were done using 7th edition of EVIEWS.

EMPIRICAL RESULTS

Descriptive Statistics

The distributions of scores are displayed in figures 1, 2 and 3 below. The overall mean score is 850.3, male mean score is 845.2 and female mean score is 856.3. Thus, the average of female student score is about 1.1 percentage point higher than male student. The male students have relatively much higher variation with a standard deviation of about 120/1000 compared to only about 85/1000 for female students. However, a test of difference between the mean scores in Table 1 indicates that the difference is statistically quite insignificant.



Figure 1: Distribution of Scores (Pooled Data)



Figure 3: Distribution of Scores (Female)



Table 1: Test of Difference between Mean Scores			
Hypothesis Test: Independent Groups (t-test, unequal variance)			
maleSc	femSc		
845.19	856.28	mean	
119.97	85.15	std. dev.	
166	142	n	
	296	df	

Table 1: Test of Difference between Mean ScoresHypothesis Test: Independent Groups (t-test, unequal variance)			
	11.73728	standard error of difference	
	0	hypothesized difference	
	-0.94	t	
	.3455	p-value (two-tailed)	

The distributions of total online time use over the semester (in minutes) for pooled data, male and female students are shown in Figures 4, 5 and 6, respectively.



Figure 4: Distribution of Time Use (Pooled)



Journal of Economics and Economic Education Research, Volume 13, Number 3, 2012





On average a female student spends about 4529 minutes online over the semester while a male student spends about 4633 minutes with the average for the two of 4585 minutes or 76.4 hours. The gender difference of 104 minutes over the semester is statistically quite insignificant as demonstrated in Table 2.

Table: 2 Test of Difference between Mean Time uses			
Hypothesis Test: Independent Groups (t-test, unequal variance)			
	maletm	femtm	
	4633.18	4528.86	mean
	1873.82	1694.89	std. dev.
	166	142	n
		305	df
		104.32000	difference (maletm – femtm)
		203.42507	standard error of difference
		0	hypothesized difference
		0.51	t
		.6084	p-value (two-tailed)

The correlation between score and time use for pooled data is reported in Table 3 which shows that the correlation is 0.59 and is highly significant statistically. The results for male and female students are very close and, therefore, are not reported here.

Table 3: Correlation between Online Time Use and Score				
Sample:		1 308		
Included observations:	Included observations: 308			
	Correlation			
t-Statistic				
Probability	SC	TM		
SC	1.000000			
ТМ	0.585637	1.000000		
t-value	12.63855			
p-value	0.0000			

The Estimated Linear Regression Model

Table 4 reports the results of estimating the Linear Regression model.

Table 4: Linear Mixed Dummy Model				
Dependent Variable: SC				
Method: Least Squares				
Sample:				1 308
Included observations:				308
Variable	Coefficient	Std. Error	t-Statistic	Prob.
ТМ	0.037718	0.003541	10.65322	0.0000
GE*TM	-0.007683	0.005520	-1.392000	0.1649
GE	49.82585	27.05056	1.841952	0.0665
С	670.4318	17.68725	37.90481	0.0000
R-squared	0.351952	Mean dependent var		850.3019
Adjusted R-squared	0.345557	S.D. dependent var		105.3423
S.E. of regression	85.21943	Akaike info criterion		11.74124
Sum squared resid	2207755.	Schwarz criterion		11.78968
Log likelihood	-1804.151	Hannan-Quinn criter.		11.76061
F-statistic	55.03370	Durbin-Watson stat		2.008895
Prob(F-statistic)				0.000000

This model explains 35.2 % of variation and 34.6 % of variance in Score, The F- value shows that Coefficient of Determination R^2 is highly significant. The slope coefficient of time use is highly significant while the coefficient of gender (Intercept Dummy) is significant only with α at 10% level. The coefficient of Slope Dummy is insignificant. Thus, the impact of time use on score is highly significant but that of Gender is not significant according to this model.

Page 72

We found, however, that the second model, which is more successful (as reported below), shows significant contribution of Gender.

Durbin Watson Statistic shows lack of the problem of auto-correlation. We have also performed Heteroscedasticity test using Harvey's method as reported in Table 5 below. The Harvey's test regresses logs of squared residuals on the original regressors. Harvey's test shows lack of the problem of Heteroscedasticity with respect to any regressor.

Table 5: Test of Heteroscedasticity				
Heteroskedasticity Test: Harvey				
F-statistic	1.084411	Prob. F(3,304)		0.3559
Obs*R-squared	3.261141	Prob. Chi-Square(3))	0.3531
Scaled explained SS	3.124172	Prob. Chi-Square(3))	0.3729
	Tes	st Equation:		
Dependent Variable:		LRESID2		
Method:		Least Squares		
Date: 02/17/12		Time: 18:17		
Sample:				1 308
Included observations:				308
Variable	Coefficient	Std. Error	t-Statistic	Prob.
С	6.418806	0.450638	14.24382	0.0000
ТМ	0.000139	9.03E-05	1.534351	0.1260
GE*TM	-8.19E-05	0.000140	-0.584241	0.5595
GE	0.189423	0.682795	0.277423	0.7816
R-squared	0.010588	Mean dependent var		6.970303
Adjusted R-squared	0.000824	S.D. dependent var		2.177829
S.E. of regression	2.176931	Akaike info criterion		4.406611
Sum squared resid	1440.665	Schwarz criterion		4.455054
Log likelihood	-674.6182	Hannan-Quinn criter.		4.425981
F-statistic	1.084411	Durbin-Watson stat		1.980357
Prob(F-statistic)				0.355902

Interpretation of Model 1 results:

We have,

$$\hat{\mathbf{Sc}} = 670.432 + 0.038$$
Tm - 0.008Ge*Tm + 49.826Ge (4)

The slope coefficients indicate that an increase of 100 minutes in time use over the semester would cause predicted score to rise by 38 out of 1000 for a male student only 30 out of 1000 for female students. Since the coefficient of Slope Dummy is insignificant we cannot read much into this small gender difference in the expected reward for increased online time use. In order to examine the role of the intercept terms we will try to estimate the predicted score when a student has minimal time use. When online Time use over the semester is only about 553 minutes (which is the lowest value in the sample and is also nearly equal to the time taken by the Midterm and Final tests) the expected score for a male student is around 691 out of 1000 or 69.1%), and for a female student it is around 736/1000 showing a small difference of about 45 points out of 1000 (or 4.5%). However, as mentioned above, the contribution of Gender to intercept is significant only at 10% level. In the case of the second model, however, the conclusions about gender effect are quite strong.

The Estimated Constant Elasticity or Double-Log Regression Model

Table 6: Constant Elasticity (Double Log) Model				
Dependent Variable				: LOG(SC)
Method:				Least Squares
Date: 02/17/12				Time: 18:11
Sample:				1 308
Included observations:				308
Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG(TM)	0.426926	0.027708	15.40781	0.0000
GE*LOG(TM)	-0.177090	0.046398	-3.816787	0.0002
GE	1.506889	0.387743	3.886311	0.0001
С	3.150760	0.231738	13.59620	0.0000
R-squared	0.482983	Mean dependent va	r	6.729786
Adjusted R-squared	0.477881	S.D. dependent var		0.223962
S.E. of regression	0.161830	Akaike info criterio	-0.791641	
Sum squared resid	7.961422	Schwarz criterion	-0.743198	
Log likelihood	125.9127	Hannan-Quinn criter.		-0.772271
F-statistic	stic 94.66292 Durbin-Watson stat			1.971302
Prob (F-statistic)				0.000000

Table 6 reports the results of estimating the Log-Linear Regression model.

The model has much larger \mathbb{R}^2 as well as $\overline{\mathbb{R}}^2$ indicating that the model can explain 48.3% of variation and 47.8% of variance in log of Score. All the coefficients are highly significant

showing strong time use and gender effects on score. The F-statistic is quite high and the Akaike and Schwarz criteria are far better than the above model. The test for Heteroscedasticity was not carried out for this model as the regressor time is scaled down by taking log. The DW statistic shows lack of auto-correlation.

Interpretation of Model 2 results:

We have,

$$\log S_{c} = 3.151 + 0.427 \log(Tm) - 0.178 Ge^* \log(Tm) + 1.507 Ge$$
(5)

The double-log model provides some quite interesting results. First, the elasticity with respect to male student is 0.43 indicating that a 10% increase in Time use is expected to result in an increase of about 4.3 % of "existing" score (which will be slightly less than 4.3 percentage point because the "existing" score will be less than 100%). This is quite encouraging! Roughly speaking, a male student who is marginally (say 10%) below letter grade A could jump to A by making about 30% more efforts as measured by time use (given the assumption of this study that overall effort is proportionately related to online Time use). For a female student the prospect is good but a little dampened because of the negative Slope Dummy. For a female student the elasticity is 0.43 less 0.18 or 0.25. Thus a 10% increase in Time use is predicted to improve existing score by 2.5% as compared to 4.3% for male students. Moreover, the gender difference is also statistically quite significant. Thus, for example, an improvement of 10 percentage point in score would require an increase in Time use by nearly 50%. For an improved letter grade this is not a bad deal, provided the student has available time to use.

In order to see the use of the intercept we will try to estimate the predicted score when a student uses minimal online time use. If a male student spends only 553 minutes in online time use over the semester, the predicted score, using (natural) anti-log function comes to only about 346 out of 1000, or letter grade F. For a female student with similar time use the predicted score jumps to a little over 500, but is still letter grade F. These predictions are much lower than those of the above model.

The Estimated Decreasing Elasticity or Linear-Log Regression Model

Table 7 reports the results of estimating the Log-Linear Regression model.

Table 7: Decreasing Elasticity (Linear-Log) Model				
Dependent Variable:				SC
Method:				Least Squares
Date: 02/21/12				Time: 23:31
Sample:				1 308
Included observations:				308
Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG(TM)	209.9604	11.36220	18.47884	0.0000
GE*LOG(TM)	-37.19491	19.08718	-1.948685	0.0523
GE	321.5180	159.6213	2.014254	0.0449
С	-908.4865	95.04119	-9.558871	0.0000
R-squared	0.607490	Mean dependent var	r	850.3019
Adjusted R-squared	0.603616	S.D. dependent var	105.3423	
S.E. of regression	66.32243	Akaike info criterio	11.23984	
Sum squared resid	1337194.	Schwarz criterion	11.28828	
Log likelihood	-1726.935	Hannan-Quinn criter.		11.25921
F-statistic	156.8341	Durbin-Watson stat	1.942221	
Prob(F-statistic)				0.000000

The Decreasing Elasticity model has the largest \mathbb{R}^2 as well as \mathbb{R}^2 indicating that it can explain 60.7% of variation and 60.3% of variance in Score which is quite high for a cross-sectional study where numerous individual characteristics are at play but only a couple are measured and used. The F-statistic exhibits high statistical significance of the coefficient of Determination. The coefficient of Log(Time) is highly significant , but the coefficients of other regressors have lost some statistical significance compared to the previous (double-log) model. Now, the Slope Dummy coefficient is significant only at 10% while Intercept Dummy is significant at 5% levels. Similarly, the Akaike and Schwarz criteria have become high (or worse) compared to the previous model. The DW statistic is still near 2. The Heteroscedasticity test for this model too was not performed for the reason mentioned above.

Interpretation of Model 3 results:

We have,

 $\hat{\mathbf{Sc}} = -908.487 + 209.960\log(\text{Tm}) - 37.195\text{Ge*}\log(\text{Tm}) + 321.518\text{Ge}$ (6)

The elasticity with respect to log(Tm) for a male student is 209.960/Sc, which continuously decreases as the level of score increases. For a minimal level of Time use of 553

minutes over the semester the calculated elasticity 209.960/553 or equal to 0.38, indicating that such a male student is expected to improve the score by 3.8% of existing score with additional 10% online time use. Plugging the values, the predicted score for a male student with minimal online time use is only 417/1000 which is only 7.1 percentage point above the previous model but is still letter grade F. On the other hand, a male student with time use around the overall mean of 4585 minutes will have elasticity only 209.96/4585 equal to 0.05 indicating that a further 10% increase in Time use is predicted to improve the score by only 0.5% of existing score. The predicted score for such a student is midway between letter grade B and letter grade A. For a student with even higher level of time use, the reward for additional online time use will be obviously pretty low.

Similarly, for a female student with online time use of only 553 minutes the elasticity comes to (209.96- 37.195)/553 equal to 0.31 indicating that a 10% increase in time use is expected to improve the existing score by 3.1% of existing score. The predicted score for such a female student is, however, 86.6/1000 above a similar male student or equal to 504/1000 which is pretty close to the prediction of the previous model. Thus a female student too, with minimal online time use can significantly improve her score with additional efforts. Again the elasticity continuously declines as the online time use level increases, with values close to those of the male students. In fact, the gender difference in elasticity also declines as the level of score increases.

CONCLUSIONS

This study uses actually recorded online time use of students instead of self-reported surveys used in most studies in the relevant literature. Moreover, the models use actual scores instead of the letter grades which not only hide a lot of information by converting the ratio scale variable to discrete ordinal variable. As a result, this study could safely use various forms of Multiple Regression models. A basic assumption underlying this study is that online time use is objectively measurable and good indicator of overall effort by students in online classes. The evidences suggest that there is a significant reward for additional effort, especially at the lower levels of times use and scores. The Constant Elasticity model predicts a 4.3% improvement in existing score for additional 10% increase in online time use for male students. For female students the improvement is expected to be only about 2.5% in existing score. The gender difference is highly significant statistically in the Constant Elasticity model. The decreasing Elasticity model is not only theoretically more appealing but also most successful in explaining variations in the scores. It can explain about 60% of variation in scores, which is quite high for a cross-sectional study where numerous individual characteristics are at play while only a couple of attributes are measured and used.

However, the gender difference gets dampened and loses some of its statistical significance in the Decreasing Elasticity model compared to the Constant Elasticity model.

According to the decreasing Elasticity model, a 10% increase in online time use for male students with minimal online time use, is expected to improve the existing score by 3.8% of existing score. For a similar female student the predicted improvement is 3.1% of existing score. As the level of time use increases to the mean level (4585 minutes over the semester or 76. 4 hours), the elasticity for male students drops to 0.05 indicating that a 10% increase in time use would be expected to improve existing score only by 0.5%. The gender difference becomes very small at higher levels of time use. The results of this study are particularly significant for students with low online time use. Instructors should encourage such students to significantly increase their effort as it promises much larger reward. Although few students can and have achieved high scores despite their low online time use, it is clear from the data that very low online time use is a good predictor of low scores with few exceptions. This study can be easily extended by incorporating other objectively measurable attributes of the students, such as their previous GPA, Race, Level of Education (Graduate vs. Undergraduate) and also covering other subjects.

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Page 80