Student Effort, Consistency, and Online Performance

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Abstract

This paper examines how student effort, consistency, motivation, and marginal learning, influence student grades in an online course. We use data from eleven Microeconomics courses taught online for a total of 212 students. Our findings show that consistency, or less time variation, is a statistically significant explanatory variable, whereas effort, or total minutes spent online, is not. Other independent variables include GPA and the difference between a pre-test and a post-test. The GPA is used as a measure of motivation, and the difference between a post-test and pre-test as marginal learning. As expected, the level of motivation is found statistically significant at a 99% confidence level, and marginal learning is also significant at a 95% level.

Literature Review

The role of study time or effort determining student grades or GPAs has been investigated for many years and the results obtained have been mixed, from the expected positive, although moderate, relationship found in early studies (Allen, Lerner, & Hinrichsen, 1972; Wagstaff & Mahmoudi, 1976) to positive but insignificant (Schuman, Walsh, Olson, & Etheridge, 1985) and even negative (Greenwald & Gillmore, 1997; Olivares, 2000). Early studies reported correlation coefficients between study time and grades; later studies, such as the one done by Schuman et al. (1985), added independent variables like aptitude measures (SAT) and self-reported attendance and used much larger samples sizes (424 students) during a period of ten years (1973-1982). Schuman et al. (1985) concluded that study time was not a significant factor explaining grades or GPAs, but the paper has served as a major reference in the field. One subsequent paper (Rau & Durand, 2000) observed that the lack of association found in the Schuman paper was due to invariability of its SAT scores influenced by the selectivity of the sample (University of Michigan). They used a sample of 252 students from the Illinois State University and found a positive relationship between GPAs and a constructed index based on study time, study habits and academic orientation. Another related study (Michaels & Miethe, 1989) found a positive relationship between study time and grades and suggested that the Schuman findings might have contained specification errors. The authors added to their model a total of fourteen dummy variables: five “quality of study time” variables and nine background or control variables such as gender, years in college, field of study, etc. However, the positive relationship was significant only among freshmen and sophomores. Yet another paper (Olivares, 2000), also arguing specification errors in the Schuman paper, added other variables like course difficulty level, grade inflation, and student cognitive ability, and found that study time and grades are negatively and significantly related.

All of the articles listed above have three things in common. First, they used surveys to obtain self-reported data. Second, they used a regression technique called stepwise regression. Third, their reported R-squares oscillated between 0.10 and 0.20, which is a relatively small percent of student performance variance explained by the independent variables used.

Student performance has also been analyzed in online courses. Some studies have continued using web questionnaires or surveys (Cheo, 2003; Williams & Clark, 2004; Michinov, Brunot, Le Bohec, Jacques, & Marine, 2011) while others have continued using the stepwise regression approach (Ramos & Yudko, 2008; Waschull, 2005). Using the information obtained either from surveys or the web-base system used in the course, these studies have concentrated on explaining grades with student participation (Ramos & Yudko, 2008), procrastination (Michinov, Brunot, Le Bohec, Jacques, & Marine, 2011; Wong, 2008), student ratings of instructor and course quality (Johnson, Aragon, Shaik, & Palma-Rivas, 2000) and time-management (Taraban, Williams, & Rynearson, 1999; Wong, 2008).

Method

As indicated above, the studies that have analyzed the relationship between grades and study time, quality of time, procrastination level, student ratings, and time-management skills, have used surveys to obtain that information. However, there has been some evidence indicating that the use of surveys may lead to respondents lying or exaggerating their responses, especially when the information involves possible embarrassment, punishment, or reward. Some researchers have found that survey responses are not reliable when workers report hours worked (Jacobs, 1998), consumers report amount of drugs used (Harrell, Kapsak, Cisin, & Wirtz, 1986), and students their study time distribution (Taraban, Williams, & Rynearson, 1999). Another technical paper (Stinebrickner & Stinebrickner, 2004) demonstrates how the reported errors from survey questions can be relatively significant, discusses how the estimators can be improved, but warns about the inaccuracies of the results obtained from such samples. On the other hand, the stepwise regression method used by most studies cited above, is not a reliable method since it leads to bias estimates (Kennedy, 2008, p. 49; Leamer, 2007, p. 101).

Due to the findings stated above, we do not estimate our dependent variable using surveys, nor do we use a stepwise regression method. Instead, we just use the time spent online as a measure of effort. In that sense, we follow the approach used by Damianov et al. (2009), who found a positive and significant relationship between time spent online and grades, especially for students who obtained grades between D and B. They obtained their results using a Multinomial

Logit Model (MNLM), which they argue being more appropriate than Ordinary Least Squares (OLS) (Damianov, Kupczynski, Calafiore, Damianova, Soydemir, & Gonzalez, 2009, p. 2) when using letter grade as dependent variable. Our paper, however, uses the OLS technique because our dependent variable is the numerical final grades obtained in the courses, and unlike the stepwise regression approach, we use all the variables in a single model. While the use of OLS would be inappropriate when the dependent variable is a discrete variable (Spector & Mazzeo, 1980), this is not a problem with our model since our grades are continuous.

Variables and Model

Our sample consists of 212 students who were enrolled in 11 microeconomic courses offered online by an accredited University located in Florida, during the academic year 2009-2010. On the other hand, given that the amount of minutes per day were available for each student during the one-month intensive courses, we use the total minutes spent online as one explanatory variable, and calculated coefficients of variation of those minutes, the ratio of the standard deviation to the mean times one hundred, to estimate student consistency as a second explanatory variable. This variable is our measure of quality of time or time-management skills. Relatively lower values of the coefficient of variation are evidence of higher consistency or better time-management skills, and vice versa. The coefficient of variation is not sensitive to extreme values, so it allows us to compare student usage of time given different levels of effort. A third explanatory variable is the students cumulative Grade Point Average or GPA, which we suggest as a measure of student motivation. Our fourth independent variable is the difference between a pre-test and post-test, which consists of twenty multiple-choice identical questions. The students take the pre-test and are not able to see their grades until the end of the course, and they are not aware that the same questions will be asked at the end of the course in the post-test. The difference between those two tests divided by the SAT scores of each student has been used before as a measure of "scholastic effort" (Wetzel, 1977, p. 36). However, we did not have access to the SAT scores, so we just call this variable "marginal learning".

Our regression equation is: $Yi = \alpha0 + \alpha1Xi1 + \alpha2Xi2 + \alpha3Xi3 + \alpha4Xi4 + \varepsilon i$ where Yi is the grade obtained in the course by the ith student, Xi1 is the student's GPA, Xi2 is the difference between the grades obtained by the ith student in a pro-test and a pre-test, which contain twenty multiple-choice questions identical to each test, Xi3 is the amount of time spent by the ith student during the course in minutes, and Xi4 is the coefficient of variation of time used by the ith student during the course. The letters α0 and εi are the corresponding intercept and error terms.

Data

Our data set consists of four-week Microeconomics courses at an online accredited University located in Florida. The University uses the Learning Management System known as Angel and it keeps records of the amount of minutes the students spend online per day. Each course has approximately an average of 19 students, and our database does not include the students who either did not log in after the second week of classes or did not take the final exam and/or the post-test. Grades are the numerical grades obtained after completion of the course. We do not include grades from students whose GPA were reported as zero. The Post-test – Pre-test variable is the difference between an exit and entry test, which contain identical questions. Such variable was allowed to contain only non-negative values since negative values are usually due to students not taking the post-test, which would have introduced a bias in our results. "Total minutes" is the final amount of logged-in minutes the students spent from the first day of classes until completion of the course. Finally, the Coefficient of Variation is the ratio of the standard deviation to the mean amount of minutes after completion of the course, expressed as a percent. Tables 1 and 2 below show an overall summary statistics for each variable, and an average for each value per course respectively.

TABLE 1: Data Summary

Variable	Mean	Median	Lowest	Highest
Grades	80.8	82.09	40.35	100
GPA	3.12	3.25	1	4
Post-test – Pre-test	33.09	32.5	0	80
Total Minutes	2393	2058	413	8001
Coefficient of Variation	111.89%	107.87%	39.78%	247.12%

TABLE 2: Average Values Per Course

Course	Grades	GPA	Pre-Test	Post-Test	Minutes	C.O.V.
1	81.93	3.21	28.88	56.11	1968.88	118
2	81.14	3.30	30.78	59.47	2680.91	93.78
3	83.05	2.99	30.41	52.7	2348.35	125.89
4	78.87	3.11	36.66	62.77	2772.54	99.19
5	82.79	3.21	35.2	65.62	3010.77	98.26
6	82.98	3.08	48.68	66.84	2653.72	102.8
7	82.15	3.18	29.2	60.8	2559.62	120.12
8	78.49	3.08	28.94	47.89	2653.72	102.8
9	77.17	3.06	32.96	60.55	1811.35	120.18
10	78.75	3.07	34.07	59.81	2088.66	124.18
11	78.00	3.09	32.27	52.04	2266.45	115.62

Findings

The OLS regression results are shown in Table 3 below. Our model explains about 46% of the variance of grades. The studies cited in the literature review explained at most 20%. On the other hand, it is not surprising to find that student motivation (GPA) is positively related to grades and it is statistically significant at a 99% level of confidence. Such result is the same as early (Park & Kerr, 1990) as well as recent (Crede, Roch, & Kieszczynka, 2010) studies. A 0.10 increase in a student's GPA is expected to increase the course grade by almost one point. The most surprising result is that the amount of minutes spent online is not a statistically significant variable explaining final grades. That is consistent with the lack of influence of study time on grades reported by Schuman et al. (1985). Successful performance in online courses does not seem to be a function of the amount of time spent online or effort. On the other hand, the results also reveal something very interesting. The students who log in more frequently and with less variation of minutes per day tend to get higher grades. Table 1 shows that student consistency varies approximately between 40% and 250%. On the other hand, table 3 indicates that if, for example, a student consistency is currently 150%, an improvement to 100% would increase her final grade by an average of 2.5 points. This significant result is also found in face-to-face course research that used other measures of consistency such as attendance (Romer, 1993; Durden & Ellis, 1995) or different time-management skills (Britton & Tesser, 1991). It is also similar to online-course research that has measured consistency with page hits (Ramos & Yudko, 2008) and procrastination level (Michinov, Brunot, Le Bohec, Juhel, & Delaval, 2011).The last regressor in our model, the difference between the pro-test and pre-test grades or marginal learning, is also a significant influence on the student grades. A student whose pre-test grade is 40 and post-test is 50, should expect on average an improvement of 0.6 points in her final grade. This is a result that, in our opinion, should reflect the extent to which the objectives of the course, the pre and post tests, and the assignments and tests given during the course are consistent with each other. Even though our coefficient has the expected positive sign and it is statistically significant, its value, 0.06, is not near what a one-to-one relationship between the two tests should be. Since the range between pre and post test grades is about 80 and the range of final grades is 60, post-test minus pretest grades ideally should have a coefficient of 0.75 (60 divided by 80). We did not find any reference to this topic in the literature, but we suggest that as the coefficient approaches an expected one-to-one relationship, it might be an indicator of course-design consistency.

TABLE 3: Regression Results

	α_0 (intercept)	α_1 (GPA)	α_2 (post-pre)	α_3 (minutes)	σ_4 (COV)
Coefficient	53.2	9.46	0.06	0.0005	-0.05
p-value	2.83 E-23	7.71 E-18	0.03	0.17	0.01

R2 = 0.46. F-value = 44.07. White Test: No heteroscedasticity at 5% significance level. Residuals show an approximately normal distribution indicating any unexplained variation is due to randomness.

Conclusions and Recommendations

As indicated in the beginning of this paper, the relationship between effort, as measured by study time, and grades is not clear. We did not rely on self-reported study time and instead used the recorded amount of minutes students spent logged into the courses as a proxy for effort. Our results support the evidence that effort is not a significant influence on grades. However, the coefficient of variation of time, or our measure of student consistency, is a significant influence on grades. As the coefficient of variation is reduced by 10 percent, the overall grade is increased by 0.5 points. Such result is crucial for administrators, advisors, and students. The students should learn that it is not the amount of time logged in that is important to get good grades, but how frequent and stable the amount of minutes is. Student advisors should emphasize that "studying hard" (total minutes) is not as important as "studying smart" (consistency).

Administrators who focus on the amount of minutes spent online as a measure of institutional success, should also consider the coefficient of variation of those minutes. Lower coefficients of variation should be a higher priority than high amounts of minutes. Finally, the difference between a pre-test and a post-test could be used as a measure of course consistency with goals and objectives. A well designed course should contain assignments and tests that evaluate learning of objectives. If the questions on the pre-test and post-test are consistent with the questions asked on quizzes, mid-term and final exams, and these in turn are also consistent with the course objectives, the regression coefficient of a post-test minus pre-test should reflect a one-to-one relationship with the final grades. The extent to which the resulting coefficient approximates an expected one-to-one relationship could be used as a value of teaching effectiveness. Since the same microeconomics course has just been redesigned with precisely the purpose of making all assignments and tests more consistent with new goals and objectives, the regression shown in this paper will be done again with the purpose of testing such hypothesis. Hopefully, our model also will incorporate more variables indicating how individual students use their time during the one-month course while taking tests and doing different assignments.

References

Allen, G., Lerner, W., & Hinrichsen, J. J. (1972). Study behaviors and their relationships to test anxiety and academic performance. Psychological Reports (30), 407-410.

Britton, B. K., & Tesser, A. (1991). Effects of Time-Management Practices on College Grades. Journal of Educational Psychology , 83 (3), 405-410.

Cheo, R. (2003). Making the Grade through Class Effort Alone. Economic Papers, 22, 55-65.

Crede, M., Roch, S., & Kieszczynka, U. (2010). Class Attendance in College: A Meta-Analytic Review of The Relationship of Class Attendance With Grades and Student Characteristics. Review of Educational Research, 80 (2), 272-295.

Damianov, D., Kupczynski, L., Calafiore, P., Damianova, E., Soydemir, G., & Gonzalez, E. (2009). Time Spent Online and Student Performance in Online Business Courses: A Multinomial Logit Analysis. Journal of Economics and Finance Education, 8 (2), 11-19.

Durden, G. C., & Ellis, L. V. (1995). The Effects of Attendance on Student Learning in Principles of Economics. American Economic Review , 85 (2), 343-346.

Greenwald, A., & Gillmore, G. M. (1997). No pain, no gain? The importance of measuring course workload in student ratings of instruction. Journal of Educational Psychology , 89 (4), 743-751.

Harrell, A., Kapsak, K., Cisin, I. H., & Wirtz, P. W. (1986). The Validity of Self-Reported Drug Use Data: The Accuracy of Responses on Confidential-Administered Answered Sheets. Social Research Group, The George Washington University. National Institute on Drug Abuse.

Jacobs, J. A. (1998, December). Measuring time at work: are self-reports accurate? Monthly Labor Review , 43-52.

Johnson, S., Aragon, S. R., Shaik, N., & Palma-Rivas, N. (2000). Comparative Analysis of Learner Satisfaction and Learning Outcomes in Online and Face-to-Face Learning Environment. Journal of Interactive Learning Research. , 11 (1), 29-49.

Kennedy, P. (2008). A Guide to Econometrics (6th Edition ed.). Malden, MA, USA: Blackwell Publishing Ltd.

Leamer, E. E. (2007). A Flat World, a Level Playing Field, a Small World After All, or More of the Above? A Review of Thomas L Friedman's The World is Flat. Journal of Economics Literature (45), 83-126.

Michaels, J., & Miethe, T. (1989). Accademic Effort and College Grades. Social Forces , 68 (1), 309-319.

Michinov, N., Brunot, S., Le Bohec, O., Jacques, J., & Marine, D. (2011). Procrastination, participation, and performance in online learning environments. Computers and Education (56), 243-252.

Olivares, O. (2000). Radical Pedagogy. Retrieved December 10, 2010, from ICAAP: http://radicalpedagogy.icaap.org/content/issue4_1/06_olivares.html

Park, K. H., & Kerr, P. M. (1990). Determinants of Academic Performance: A Multinomial Logit Approach. Journal of Economic Education , 21 (2), 101-111.

Ramos, C., & Yudko, E. (2008). "Hits" (not "Discussion Posts") predict student success in online courses: A double-cross validation study. Computers and Education (50), 1174-1182.

Rau, W., & Durand, A. (2000). The academic ethic and college grades: Does hard work help students to "make the grade"? Sociology of Education (73), 19-38.

Romer, D. (1993). Do Students Go to Class? Should They? Journal of Economic Perspectives , 7, 167-174.

Schuman, H., Walsh, E., Olson, C., & Etheridge, B. (1985). Effort and Reward: The Assumption that College Grades Are Affected by Quantity of Study. Social Forces , 63 (4), 945-966.

Spector, L., & Mazzeo, M. (1980). Probit Analysis and Economic Education. Journal of Economic Education , 11, 37-44.

Stinebrickner, R., & Stinebrickner, T. R. (2004). Time-Use and College Outcomes. Journal of Econometrics (121), 243-269.

Taraban, R., Williams, M., & Rynearson, K. (1999). Measuring study time distributions: Implications for designing computer-based courses. Behavior Research Methods & Instruments , 31 (2), 263-269.

Wagstaff, R., & Mahmoudi, H. (1976). Relation of study behaviors and employment to academic performance. Psychological Reports , 38, 380-382.

Waschull, S. B. (2005). Predicting Success in Online Psychology Courses: Self-Discipline and Motivation. Teaching of Psychology , 32 (3), 190-208.

Wetzel, J. E. (1977). Measuring Student Scholastic Effort: An Economic Theory of Learning Approach. The Journal of Economic Education , 34-41.

Williams, R., & Clark, L. (2004). College Students' Ratings of Student Effort, Student Ability and Teacher Input as Correlates of Student Performance on Multiple-Choice Exams. Educational Research , 46, 229-239.

Wong, W.-K. (2008). How Much Time-Inconsistency Is There and Does it Matter? Evidence on Self-Awareness, Size, and Effects. Journal of Economic Behavior and Organization , 68 (3-4), 645-656.