HOMEWORK EFFORT AND COURSE PERFORMANCE: EVIDENCE FROM A FIELD EXPERIMENT

An Undergraduate Research Scholars Thesis

by

CECILIA MOREIRA

Submitted to the Undergraduate Research Scholars program at
Texas A&M University
in partial fulfillment of the requirements for the designation as an

UNDERGRADUATE RESEARCH SCHOLAR

Approved by Research Advisor: Dr. Steve Puller

May 2017

Major: Economics

TABLE OF CONTENTS

Page

ABSTRACT 1

CHAPTER

I. INTRODUCTION 2

II. LITERATURE REVIEW 4

Information Interventions 4

III. DATA AND METHODOLOGY 6

Data 6
Methodology 7

IV. RESULTS 9

V. CONCLUSION 14

REFERENCES 15

ABSTRACT

Homework Effort and Course Performance: Evidence from a Field Experiment

Cecilia Moreira
Department of Economics
Texas A&M University

Research Advisor: Dr. Steve Puller
Department of Economics
Texas A&M University

We conduct a field experiment at Texas A&M in which students enrolled in an online course are provided information about the correlation between homework effort and exam scores via a one-time email. Due to randomization of assignment to treatment, we are able to estimate the causal effects on student performance. We find that this information intervention has no significant impact on student homework, quiz, and exam grades.

CHAPTER I

INTRODUCTION

The six year college graduation rate for full-time undergraduate students who began their studies at a four-year degree granting institution in 2008 was 60%. The graduation rate varies by the type of institution - whether it is a public, private or for profit, with 58, 65, and 27 respectively (NCES). Currently, there exist two commonly accepted theories that explain the college attrition problem. Tinto's dropout theory (1975) suggests that college persistence is more than an individual's past educational experiences and individual characteristics. One's decision to withdraw from a university is due to the lack of academic and social integration into the collegiate system. Course performance as measured by GPA is often used as proxy of an individual's academic integration into the college. Course performance has also been shown to be a strong determinant of college persistence (Stinebrickner, 2012)

During the 2017 spring semester, we conducted a field experiment at a large public state university to test the effect of providing information on the correlation of homework effort on three academic outcomes. Our subjects are undergraduate students enrolled in an online principles of economics course during the spring semester. At the commencement of the experiment, course enrollment was 547. We use a pure randomization strategy to assign subjects into one treatment and one control group. Students in the treatment group receive a one-time email sent by the course instructor on the correlation of homework effort and course performance. The email was sent after students had already taken and received a grade for the first of three course exams. The timing of the intervention is important as this allowed students to better understand how their current effort level translates to their overall course grade.

The effect of the information intervention is tested by observing three outcome variables. During the course of the semester, we observe students grades on problem sets (homework), quizzes, and exams. There are 8 problem sets, 72 quizzes, and three exams administered throughout the semester. We hypothesize that if students underestimate the relationship between homework effort and exam performance, individuals who receive this information will adjust their behavior, exert more effort on homework, and perform better overall in the course. In this case, we would expect to see a positive difference in overall grades between the treatment and control groups. On the other hand, if students have priors that overestimate the effect of homework effort on exam grades, the information provided could reduce student effort and course performance. If students hold accurate beliefs of the relationship between homework effort and exam grades, the information provided would not lead to changes in exerted effort by students.

We think this is an important question with potential benefits to students and universities. First, if students hold inaccurate priors of the relationship between homework effort and course performance, providing this information could lead to increased student effort, better understanding of course content, and higher overall grades. If effective, this low cost intervention could be easily implemented by course instructors to improve student performance in the course.

CHAPTER II

LITERATURE REVIEW

Previous research in the economics of education literature has used similar strategies to attempt to improve student achievement. The type of interventions used range from information interventions, as utilized in this paper, to information interventions combined with financial and non-financial incentives.

Information Interventions

Caroline Hoxby and Sarah Turner (2013) provide low-income high achieving students individualized information on the college application process and estimated cost of attendance using a randomized control trial. Students randomly assigned to receive this information were more likely to apply to colleges that better matched their academic potential than those in the control group, or those who did not receive the information. Hoxby's paper suggests that students who become better informed change their behavior based on the information they receive.

Barr and Turner (2016) study the effect of a nationwide initiative aimed at increasing higher education amongst adults who receive unemployment insurance. The authors exploit variation within and across states of when the letter was sent to estimate the causal effect of this information on college enrollment. Their findings suggest that individuals who received this letter are four to five percentage points more likely to enroll at a higher education institution.

Financial and Non-Financial Incentives

Levitt et al. (2012) explore the effects of immediate and delayed financial and non-financial incentives for high school students in a low-stakes test across three different school districts. The authors find positive results for immediate rewards increase student performance by .07-.08 standard deviation. In contrast, delayed rewards have no impact on student performance. This suggests that students have high discount rates (see Bettinger, 2011)

CHAPTER III

DATA AND METHODOLOGY

Data

We collect individual level panel data of students enrolled in an online principles of economics course from a large public university. At the time the treatment is rolled out, the number of students enrolled in the course is 542. We use pure randomization to assign students into one treatment and one control group. Our treatment group consists of 268 students (49.36 %), control group 274 (50.64%) students. Prior to the intervention, students in the course have similar scores in four academic measures. Students in the treatment group have problem set averages of 73.33%, while those in the control group have averages of 72.74%. Quiz averages are 78.16% and 78.71% and mean exam one grades of 75.74% and 75.87% for the treatment and control groups respectively. Similarly, students in the treatment and control groups have spent an average of 42 and 44 hours online prior to the intervention. None of these differences are statistically different.

Due to attrition, we observe treatment effects for 497 students, or 91.7 % of our original sample, 250 of whom are in the control and 247 in our treatment group. Our observed treatment effects are conditional on course persistence.

Table 1: Pre-Treatment Randomization Test

Treatment Status	Mean Outcomes of Interest			
	Exam 1 Score	Time Spent Online	Problem Set Scores	Quiz Scores
Control	75.74	44.48	72.74	78.51
	(18.69)	(24.38)	(20.09)	(16.36)
	273	274	273	273
Treatment	76.20	42.02	73.33	78.83
	(18.69)	(25.01)	(18.01)	(15.27)
	266	268	266	266
Number of Students	539	542	539	539

Intervention

Students enrolled in an online principles of economics course were randomly selected to receive information on the correlation of homework effort on grades via a one-time email. Contents of the email were gathered from previous research by Nicholas Rupp. Half of class randomly assigned to have mandatory weekly homework assignments while the other half – homework not required. Students in the control group still had access and the option to complete homework assignments, however they were not counted for a grade.

Methodology

We conduct a randomized control trial (RCT) to test the causal effect of treatment on four main variables of interest: time spent online, exam grades, quiz grades and problem set grades. By randomly assigning students into the treatment and control groups, we can estimate the effect of treatment on our outcome variables by running the following regression:

$$\gamma_i = \beta_0 + \theta TREAT_i + \varepsilon$$

Where,

γ_i represents one of our four outcome variables for individual i. In this model, θ is our coefficient of interest and is our estimated treatment effect. Due to the pure randomization strategy implemented in the research design, we expect that students in the treatment and control groups are otherwise similar. We test this assumption by comparing the means of academic performance measures between both groups. As shown in Table 1, students appear to be similar on observables. This implies that we can do a comparison of means to obtain an unbiased estimate of the treatment effect on our academic outcomes of interest.

CHAPTER IV

RESULTS

The main results of our field experiment are described and organized by outcomes of interest, quiz scores, exam scores, and time spent online. For this analysis, we only observe outcomes for individuals who remain enrolled in the course. Therefore, our results are conditional on course persistence.

Quiz Scores

To obtain an estimate of the effect of the treatment on quiz scores we regress the following equation:

$$Postquiz_i = \beta_0 + \beta_1 Treat_i \qquad (1)$$

$$Postquiz_i = \beta_0 + \beta_1 Treat_i + \beta_2 Prequiz_i \; (2)$$

The outcome of interest,$Postquiz_i$, is $student\ {}_i's$ average quiz score after treatment, $Treat_i$ is a binary variable indicating 1 if $student\ {}_i$ is in the treatment group and 0 if in the control group, and β_2 , in the second regression, is a control variable for a student's quiz average prior to treatment.

Table 2: Treatment Effect on Quiz Scores

	All	All	Pre-Treatment High Performer	Pre-Treatment Low Performer
	(1)	(2)	(3)	(4)
Treatment	-0.726	-0.135	-1.577	0.392
	(1.01)	(0.41)	(0.97)	(1.81)
Pre-Treatment Quiz		.917***		
		(0.04)		
Constant	81.704***	6.932*	85.107***	77.302***
	(0.71)	(3.17)	(0.58)	(1.34)
R-squared	(0.00)	0.83	0.01	(0.00)
Number of Observations	497	497	280	217

Asterisks indicate statistical significance at the * 0.05, **0.01, ***0.001. Standard error in parenthesis.

We estimate the effect of the treatment on quiz scores and find that students assigned to the treatment group, on average, scored .726 points less than students in the control group (1). When we control for a students' pre-treatment quiz grades, students in the treatment group score .135 points fewer than students in the control group (2). Regressions (3) and (4) estimate the treatment effect separately for students who were low and high performing prior to treatment. We categorize students who performed above the mean on the exam prior to treatment as high performing and students whose score was below the mean as low performing. The treatment effect on quiz scores for high performing students is -1.577 while the treatment effect for low performing students is .392 points. None of the estimated treatment effects are statistically different from zero.

Exam Scores

To obtain an estimate of the effect of the treatment on exam scores, we regress the following equations:

$$Exam2_i = \beta_0 + \beta_1 Treat_i \quad (3)$$

$$Exam2_i = \beta_0 + \beta_1 Treat_i + \beta_2 Exam1_i \quad (4)$$

The outcome of interest, $Exam2_i$, is $student\ _i's$ exam two score, $Treat_i$ is a binary variable indicating 1 if $student\ _i$ is in the treatment group and 0 if in the control group, and β_2 is a control variable for a student's exam 1 score.

Table 3: Treatment Effect on Exam Scores

	All	Exam 1 Control	Pre-Treatment Above Average	Pre-Treatment Below Average
	(1)	(2)	(3)	(4)
Treatment	-0.201	-0.408	0.747	-1.381
	(1.34)	(1.02)	(1.42)	(1.89)
Exam 1		.667***		
		(0.03)		
Constant	76.773***	24.298***	83.073***	68.624***
	(0.95)	(2.84)	(1.00)	(1.34)
R-squared	(0.00)	0.42	(0.00)	(0.00)
Number of Observations	497	497	280	217

Asterisks indicate statistical significance at the * 0.05, **0.01, ***0.001. Standard error in parenthesis.

Table 3 shows the results of regressions (1) and (2). On average, students assigned to the treatment group score .201 (1.23) points lower on their exam than students assigned to the control group. When we control for a students' previous exam performance, students assigned to the treatment group score, on average, .408 (.87) points lower on their exam than students in the control group. We further estimate the effect of the treatment on exam scores by observing students in the top and lower half of the exam grade distribution prior to treatment. The mean grade for the first exam, prior to treatment, was 80.95. Using this cutoff, we separate students into two categories, high performers and low performers.

Column 3 of Table 3 shows that for students who scored above average on their first exam, being assigned to the treatment group improves their exam scores by .747 points. The estimated treatment effect for students who scored below average on their first exam is -1.381. All our estimates of the treatment effect on exam score are statistically insignificant.

Time Spent Online

To obtain an estimate of the effect of the treatment on hours spent on the classes' website, we regress the following equations:

$$Posttime_i = \beta_0 + \beta_1 Treat_i \quad (5)$$

$$Posttime_i = \beta_0 + \beta_1 Treat_i + \beta_2 Pretime_i \quad (6)$$

The outcome of interest, $Posttime_i$, is the aggregate amount of hours $student_{\ i}$ spends on the classes' website after the treatment, $Treat_i$ is a binary variable indicating 1 if $student_{\ i}$ is in the treatment group and 0 if in the control group, and β_2 is a control variable for a student's aggregate amount of time spent online prior to treatment.

Table 4: Treatment Effect Time Spent Online

	All (1)	All (2)	Pre-Treatment High Performer (3)	Pre-Treatment Low Performer (4)
Treatment	(1.276)	(0.301)	-3.692*	1.304
	(1.10)	(0.71)	(1.49)	(1.67)
Time Pre-Treatment		.396***		
		(0.01)		
Constant	19.358***	1.733*	22.986***	17.384***
	(0.77)	(0.81)	(1.05)	(1.18)
R-squared	0.00	0.59	0.02	(0.00)
N	542	542	280	217

Asterisks indicate statistical significance at the * 0.05, **0.01, ***0.001. Standard error in parenthesis.

We find that over the course of the semester, students who received treatment spend 1.28(1.10) hours less time online. After we control for the amount of time students spent online prior to treatment, we observe a treatment effect of -.301(.701) hours. We again break down the treatment effect between high and low performing students and find a larger negative effect for the high performing students and a slightly positive, yet insignificant effect for the low performing students.

Table 5: Short Run Treatment Effect on Time Spent Online

	All (1)	All (2)	Pre-Treatment High Performer (3)	Pre-Treatment Low Performer (4)
Treatment	-0.54	-0.26	-0.968*	0.02
	(0.283)	(0.220)	(0.399)	(0.389)
Time Pre-Treatment		.081***		
		(0.004)		
Constant	4.043***	0.30	4.453***	3.514***
	(0.199)	(0.258)	(0.281)	(0.274)
R-squared	0.01	0.40	0.02	0.00
N	497	497	280	217

Asterisks indicate statistical significance at the * 0.05, **0.01, ***0.001. Standard error in parenthesis.

Table 5 contains regression results that estimate the short run effect of the intervention on the amount of time students spend online. We obtain the amount of time spent online 3 days following the treatment and 7-10 days following treatment. Column 1 of Table 5 shows that the immediate effect of the treatment on time spent online is -.54 (.238). Adding a control for the amount of time a student spent online prior to treatment reduces our coefficient to -.26(.220). Columns 3 and 4 provide an estimate of the short run effect for high and low performers. We find that, in the short run, high performers in the treatment group reduce the amount of time spent online by -.968(.399) while low performers increase the time spent online by .02(.389).

CHAPTER V

CONCLUSION

This paper uses a randomized control trial to test the causal effect of providing students with the correlation of effort on homework and exam scores on student performance. Due to randomization, we are able to get an unbiased estimate of the effect of the treatment on students' exam, quiz, and problem set scores. We find that receiving the treatment, has a slightly negative, yet statistically insignificant effect on our outcomes of interest.

REFERENCES

Barr, A., & Turner S. (2016). “Aid and Encouragement: Does a Letter Increase Enrollment Among UI Recipients?”

Hoxby, C., & Turner, S. (2013). "Expanding college opportunities for high-achieving, low income students." Stanford, CA: Stanford Institute for Economic Policy Research.

Levitt, Steven D, John A. List, Susanne Neckermann and Sally Sadoff. 2016. "The Behavioralist Goes to School: Leveraging Behavioral Economics to Improve Educational Performance." American Economic Journal: Economic Policy, 8(4): 183-219

Stinebrickner, Todd and Ralph Stinebrickner. (2012). Learning about Academic Ability and the College Dropout Decision. Journal of Labor Economics.

Tinto, Vincent. (1975). Dropout from Higher Education: A Theoretical Synthesis of Recent Research. Review of Educational Research.

U.S. Department of Education, National Center for Education Statistics. (2016).The Condition of Education 2016 (NCES 2016-144), Undergraduate Retention and Graduation Rates.