Knowing What It Takes: The Effect of Information About Returns to Studying on Study Effort and Achievement*

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Abstract

We study the effect of providing students with information on returns to study effort in a large introductory microeconomics course. To do so, we use granular time-use data from the course's online homework module to estimate the association between study time and course performance. We use the same data as well as course outcome data to measure the impact of this information on several important outcomes, such as study effort as well as exam and overall course performance. We find that the treatment led to a 13% short-term increase in study effort for all students. We find similar effects on homework scores. Focusing on the role of beliefs about returns to study effort, we see that short term study effort greatly increased for those students who originally over-estimated their returns to study effort. In contrast, we find more long term effects for students who originally under-estimated the returns to study effort. These students outperformed students who had over-estimated the returns to study effort both on measures of exam performance as well as overall course performance. We also see strong evidence that low-income students increased their study effort through out the course, along with evidence of large effects on their exam and course performance. We see these results as signs of a dominant substitution effect, as students substitute into studying upon learning that academic achievement is now less expensive.

Key Words: Beliefs, Study Effort, Human Capital

JEL Codes: F22, J15, J21, J61.

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1 Introduction

A student's study effort is a critical component of their education production function (Stinebrickner and Stinebricker, 2004, 2008; Fraja et al., 2010; Bonesrønning and Opstad, 2015; Gneezy et al., 2019). Because of this, understanding how students make study effort decisions is of high importance for both scholars and policy-makers. These study effort decisions also contain important trade offs for students, as studying more implies less time for non-studying activities such as leisure and work (Stinebrickner and Stinebricker, 2003; Bound et al., 2010, 2012; Metcalf et al., 2019). In order to make these trade offs efficiently, students must know the returns to their study effort, or put another way, how their study effort maps onto academic outcomes such as performance on assessments and exams as well as course grades.

Previous work has shown, however, that students often have incorrect beliefs about their own education production functions (Fryer, 2016; Esroy, 2019a). Absent accurate information on their returns to study effort, students may be over or under-investing in studying, leading to inefficient tradeoffs and outcomes. While there is a large literature studying information interventions in college classes, as far as we know, no study has yet attempted to update students beliefs about their returns to study effort with information about those returns in a classroom setting. One reason for this may be that, as a researcher, study effort is challenging to investigate as obtaining a valid measure of effort is very difficult, often impractical or even impossible, depending on the setting. Furthermore, for the same reasons, obtaining an accurate measure of the actual returns to study effort is also inherently challenging. In no small part due to these data issues, we still don't know very well how students incorporate new information about the returns to study effort into their beliefs and behavior, and whether changing those beliefs leads to important changes in achievement.

In order to address these questions, we create and administer an information intervention that both elicits and shocks students' beliefs about their returns to effort in an introductory microeconomics course. To overcome the challenge of obtaining valid measures of study effort both to create the information about returns to effort as well as measure our outcomes of interest, we leverage granular time-use data derived from the course's online homework application. We document several important facts as a result of our study, including that about 80% of students under-estimate their returns to study effort. We also find that the information contained in our intervention increased study effort in the short run (2-3 weeks after intervention) by 12.6% for all students and increased median homework score by 4 percentage points, or about 16% of a standard deviation.

We also find strong heterogeneous effects based on beliefs about returns to study effort. Firstly, we see large short-term (one week after the intervention) increases in study effort for those who originally over-estimated returns to study effort, with no sign of long-term effects. In contrast, we see very consistent positive effect for those who originally under-estimated returns to study effort, resulting in a 10% increase in study time throughout the entire course. We also see divergent paths for these two groups when looking at exam and course performance. Those who originally underestimated returns to effort increased their median exam performance by almost 25% of a standard deviation as a result of treatment. Under-estimaters also increased their performance by a percentage point and a half, or almost 16% of a standard deviation in course performance. Lastly, we also find large and significant effects on study effort to low-income students, as well as evidence of large effects on exam and course performance for that group.

This paper makes contributions to several literatures. Firstly, we contribute to the literature studying student effort decisions and the effect of studying on important academic outcomes (Metcalf et al., 2019; Fraja et al., 2010; Stinebrickner and Stinebricker, 2008). Research has demonstrated that students study more when incentives to do so increase (Hishleifer, 2016; Azmat and Iriberri, 2015; Golightly, 2020). It's also been shown that students' beliefs about how much they need to study often are strong predictors of their actual study decisions (Stinebrickner and Stinebricker, 2008). The paper most similar to ours uses data from an online language platform to demonstrate that students have incorrect beliefs about returns to their effort (Esroy, 2019b,a). The author also shows that those beliefs become more accurate upon receiving information, with consequences for achievement. We contribute to this literature by positing a framework that incorporates beliefs about returns to study effort, which may be incorrect, into a study effort decision process in which students trade off between studying and non-study activities.

Secondly, this paper contributes to the literature on performance feedback, specifically by testing important hypotheses that result from it's findings. Scholars in this literature have found strong effects on achievement as a result of performance feedback (Azmat and Iriberri, 2010; Bandiera et al., 2015; Bobba and Frasinco, 2019b,a; Goulas and Megalokonomou, 2018; Brade et al., 2018; Gonzalez, 2017; Li, 2018). These papers rightly interpret these effects as a result of changing beliefs about students' own abilities. What is less clear, however, is how these changes in beliefs translate into changes in achievement. As students learn about their ability, some input into the education production function must change. The input most under the student's control, as well as the most likely to be related to beliefs about ability is one's study effort. We aim to answer how this process takes place and whether changes in beliefs about returns to study effort mimic those about returns to ability.

More specifically, we cast these changes in beliefs and subsequent study effort decisions as products of opposing income and substitution effects under a binding student time constraint. Do students feel "richer" in their ability to achieve academically, or do they substitute more into studying upon learning they are more able? The resulting effect on study effort decisions is ambiguous and depends both on the initial beliefs as well as on the effect of the performance feedback on beliefs. We discuss this framework more in section 2.

Thirdly, we contribute to the literature studying beliefs, specifically in an education setting. A large literature has emerged over the past decade which demonstrates the importance of students beliefs (Bobba and Frasinco, 2019a,b; Conlon, 2020; Wiswall and Zafar, 2015a,b; Zafar, 2011, 2013) We are the first to document heterogeneous beliefs about returns to study effort in a common educational setting; a large introductory course at a selective public four-year university. We also demonstrate that our experimental results hinge importantly on ex ante beliefs about returns to study effort, depending on whether or not student either over or under-estimated returns to study effort based on the information found in our intervention.

Lastly, we contribute to the literature studying nudges in education (Damgaard and Nielsen, 2018). Our information intervention is very much in the spirit of other papers that attempt to alter student behavior via a light-touch intervention (Li, 2018; Carrell et al., 2020; Oreopoulos et al., 2020). There have been numerous studies that implement nudges in classrooms, with varying success. We show that our “nudge” in fact does change behavior in a way that is explained by a simple framework, further demonstrating that nudges may yet play an important role in the classroom.

The rest of the paper is organized as follows; section 2 works through a simple theoretical framework that connects beliefs about returns to effort, achievement and behavior; section 3 provides details on our field experiment; section 4 describes our data; section 5 presents our results; section 6 concludes.

2 Beliefs, Effort and Achievement

To motivate our discussion of the role of beliefs in study effort decisions, consider the following utility function for students. Following Esroy (2019a), a student receives utility from both academic achievement A and leisure L. The student also allocates their time $\overline{T}$ over both study effort e and leisure time l[1]. More formally, the student solves the following constrained optimization problem:

$$\max_{A,L} \; U(A, L) \tag{1}$$

$$s.t. \; e + l = \overline{T} \tag{2}$$

We also assume that study effort maps onto academic achievement linearly. Specifically, we assume that $A = f(e) = \alpha e$. Throughout this paper we will refer to this rate α as the “returns to study effort”. For simplicity we also assume that $L = l$. Placing these equations into the optimization problem above, student’s problem becomes

$$\max_{e,l} \; U(\alpha e, l) \tag{3}$$

$$s.t. \; e + l = \overline{T} \tag{4}$$

where e^* and l^* are the solution to the above problem. Lastly, we assume the utility function

[1]There may be other dimensions of effort that we fail to capture in this stylized model, such as quality of study effort, or effort with peers. Since we are unable to incorporate these possibilities into our empirical analyses, we abstract from them here as well, although we would agree they are avenues of future study.

is strictly concave so that a unique solution exists and that marginal utility is decreasing for both arguments. Under this framework, the student faces a linear budget constrain in *time*, for which they are allocated $\overline{T}$, over leisure and academic achievement. We represent the student's problem in figure 1 using the familiar graph used in studying consumption decisions in introductory economics courses.

(Insert graph)

Because effort maps onto achievement at a rate of α, the slope of the budget line is $-\alpha$. The linear axis represents both time spent on leisure, l, as well as time devoted to study effort, e, as $e = \overline{T} - l$. As in consumer theory, optimal effort and leisure are found where the student's indifference curve is tangent to the budget line, or more formally where $MU_A = MU_L$. Assume also that students do not know the value of α, but have beliefs, $\hat{\alpha}$, about its value. In this paper, we explore how e^* changes when students update their beliefs about $\hat{\alpha}$.

One way to frame how student behavior might change as beliefs about returns to study effort change is in terms of "income" and "substitution" effects. Assume that a student holds beliefs about returns to study effort such that $\hat{\alpha} < \alpha$.[2] Here we assume also that the student is provided information on the true value of α such that the student fully updates their beliefs about the returns to study effort. This would lead to a rotation of the budget constraint up the vertical axis, mimicking a price decrease in the variable represented on the vertical axis. Similar to a price increase in consumer theory, this rotation leads to a new equilibrium e^* and l^* resulting from a combination of income and substitution effects.

(Graph with the rotation here)

The substitution effect in this case will lead the student to study more, as academic achievement is now "cheaper". This implies that e would increase and l would decrease. From here, the income effect makes the student study less and spend more time on leisure, as they are now "richer" in time available to them and leisure is a normal good. As a result of these two opposing effects, whether

[2] We assume here that α is the same for all students but understand that, in reality, returns to study effort are likely to be heterogeneous. This would imply that $\alpha = \alpha_i$ for each student i. In our information intervention, we provide students with the average returns across a large sample of students from a previous course. In doing so, we make a trade off between offering specific information to students with offering feasible information in the form of average returns. In the end, our aim is less to provide individualized information to students but rather shock their beliefs about returns to study effort.

the new optimal e and l are less than or greater than the original optimal levels is ambiguous. The same is true in cases where $\hat{\alpha} > \alpha$, although the income and substituion effects move e^* and l^* in the opposite directions.

(Insert graph with substituion effect and other graph with income effect).

To connect this framework back to our study, in our experiment, we elicit students' beliefs about $\hat{\alpha}$ and provide them with information about α. We then study what effect this has on study effort as well as achievement. We also focus on the role of $\hat{\alpha}$ in mitigating these effects. In doing so, we are able to qualitatively estimate the relative importance of income and substitution effects in students' study effort decisions as they learn about returns to study effort.

3 Experimental Details

We administered our information treatment during the spring quarter of 2019 in a large introductory microeconomics course at the University of California (UC) Davis. The course was delivered by the instructor to two large classes of over 350 students each, with a total enrollment of over 760 students. While we administered five total surveys (including the *baseline survey* during the first week of class as well as four surveys at the beginning of each exam), we only use results from the baseline survey and the survey administered with our information intervention (*survey two*) in this paper. All surveys were completed by hand.

The baseline survey asked students numerous questions about their beliefs about their academic ability, preferences for majors, expected grade in the course, as well as beliefs about returns to study effort. Regarding this last question, students were asked"how many hours do you think you would have to study per week to increase your grade by one letter?". The baselines survey also asked students to sign a Family Education Rights Protection Act (FERPA) release so that we could access their demographic information as well as their academic records from before their enrollment at the university.

Survey two, which was administered at the beginning of the first exam, contained our information treatment. Two types of surveys were distributed to students that day. Each survey contained a paragraph of text followed by a short yes or no question. The treatment survey contained information on the relationship between hours spent studying in that class and an increase in one letter grade calculated using data from the previous time the professor taught the course (spring 2018). More specifically, students were told that three and a half hours of study time per week was associated with an increase in one letter grade. The *control* survey described the benefits of participating in research on campus. The font and amount of text used in both treatment and control surveys were designed so that the two surveys would appear identical at a quick glance. Both the treatment and control texts can be found in the appendix.

Surveys appeared on the back of the first page of the second exam. Exams were ordered such that treatment and control surveys alternated in their placement. In section 5.1, we verify that this assignment to treatment and control groups appears to be as good as random across student characteristics. Teaching assistants handed out exams to students as they entered the classroom and took their seats. Once the class began but before the exam commenced, students were given five minutes to turn over the first page of the exam and address the questions and text in the survey. Students then ripped out the survey page and turned them into the teaching assistants.

4 Data

We use several data sources to study the effect of our information treatment on our set of outcomes. For the surveys, 456 students completed the baseline survey and 566 students completed survey two (administered at the beginning of exam one). All students who completed the baseline survey signed the FERPA release contained in the baseline survey.

Our primary analysis sample consists of students who completed both the baseline survey as well as survey one (which took place before exam one and contained the information treatment). We then match these survey responses to data on course performance including scores on all four exams, total points in the course as well as course grade. We also leverage time-use data measuring time spent on each of the nine homework assignments assigned throughout the course. These time use data are measured in seconds and offer us an extremely granular measure of study time. These data measure the time spent between the moment when a student begins the homework assignment and either completes it or exits the homework module[3].

Along with time spent on homeworks, we also capture homework scores. For the purposes of this study, we only have access to course and time use outcomes for students who signed the FERPA release. Because of imperfect overlap between the samples who completed the baseline survey and the survey administered at the beginning of the first exam, our analysis sample consists of 304 students, which represents exactly two thirds of our baseline survey sample.

5 Results

5.1 Descriptive Results

First we check that our treatment assignment was as-good-as random. As mentioned above, the physical copies of the exams from exam two containing assignment to treatment and control groups were arranged such that they alternated in placement within separate piles of all exams.

Teaching assistants distributed exams by handing out the top exam from their pile to students as they entered the room or raised their hand from their seats. While we acknowledge that this mechanism is not "random", we see no reason ex ante to think that assignment to treatment under this mechanism would lead to any significant relationships between treatment assignment and either observable or unobservable student characteristics. We test this by regressing treatment status on demographic characteristics as well as responses to our baseline survey, which contains beliefs about various features of the course and returns to effort.

We see in tables 1 and 2 that there is no statistically meaningful relationship between treatment status and any demographic characteristics. The same is mostly true when looking at responses to our baseline survey. We do see, however, a strong statistical relationship between responses on

[3] We also use the same data source from the previous time the instructor taught the course, spring 2018, to create our information treatment. To do so, we use the complete course history of time spent on homeworks for all students, comprising of 750 students, and regress time spent on homework on overall percentage points in the course. We find a statistically significant relationship between time spent on homework and course performance. More specifically, we find that three and a half hours of study time is associated with a ten percentage point increase in the course, which corresponds to an increase in one letter grade. Not surprisingly, we find an incredibly strong positive relationship in our study sample between measures of time spent on homework throughout the course and overall course performance. More specifically, we find that an increase of one unit in log time spent on homeworks increases course performance by 2.9 percentage points (p value = 0.000). Converting these results into time units, the amount of study time per week associated with a ten percentage point increase found in our study sample ranges from 3.8 to 4.5

the questions ”How many hours a week do you think you need to study to increase your grade by one letter?” and ”What grade do you expect to get in this class” with treatment status. In order to ensure our ability to estimate the causal treatment effect of our information intervention, we estimate models that include controls for responses to baseline survey questions. Broadly speaking, however, we see this as evidence that the information treatment was assigned randomly to students in our sample.

Looking at students' responses to the question ”How many hours a week do you think you need to study to increase your grade by one letter?” in figure 4, which we take to represent beliefs about returns to study effort, we see a wide dispersion across our sample. We also notice a dramatic right skewness, with numerous high-value outliers. We also see that the median study hours required to increase one's grade is six, almost twice as large as the number contained in our information treatment. Also, if we are to take our estimate of the returns to effort seriously, this implies that most of our sample (80%) over-estimates the number of hours required to increase their grade by one letter. We think of these students as under-estimating the returns to study effort, as they believe it takes more hours than necessary to increase their grade. Conversely, we have far fewer students (20%) who under-estimate the number of hours required to increase their grade, or students who over-estimate their returns to study effort[4].

We also regress beliefs about returns to study effort on our set of demographic characteristics and beliefs to investigate what variables best predict these beliefs. Looking at table 3, we see that the variables most predictive of beliefs about returns to study effort are self reported study habits (“How many hours do you study per week for a typical class?”), beliefs about how much control one has over their ability, as well as expected grade. Interestingly, we see that the more time students report studying for a typical class, the more study time the believe they need to study to increase their grade. We also see that the more control students believe they have over their ability, the

[4] Following Esroy (2019b), we also ask students about their beliefs regarding how much “control” they have over their ability. Loosely speaking, this question was meant to elicit beliefs about mindset, more specifically whether the students had what is called a “growth mindset”, or whether they believed their ability was less flexible but more fixed. Unfortunately, while we find this line of inquiry interesting were hoping to incorporate responses from students into our analyses, we do not see much variation in responses to our questions on mindset. In practice, we asked students ”How much control do you believe you have over your ability?”, with possible responses ranging between “Alot” to “Very little or none”. About 78% of students believe they have an above average amount of control or higher over their ability. One one student believed they had below average amount of control over their ability.

more likely they are to report needing fewer hours to increase their grade. This implies a positive relationship between believing you can control your ability and beliefs in greater returns to study effort.

Perhaps not surprisingly, we also see that students who expect to receive a C+ or lower in the class report needing more hours to increase their grade by one letter. Specifically, believing you will receive a C+ or lower is related to an increase in almost four hours to boost your grade. The relationship between these two variables may provide us with a glimpse as a potential mechanism for our results. Students who expect to receive low grades may have inflated beliefs about how much effort they would need to exert in order to improve their performance. This leads them to provide effort that is potentially below what they would if they knew the true returns to effort. Providing students with information that the number of hours needed to do so is actually lower than they believe may increase study effort and performance. We discuss this further in section 5.3 when we go over our results based on beliefs about returns to study effort.

Lastly, as a check on whether students paid any attention to information found in our intervention, we study the responses of students to the questions found just below the information in both the treatment and control groups. Both treatment and control messages contained a brief yes or no question below the main text. The treatment survey asked students if they found the information useful, while the control survey asked if students wanted to learn more about research on campus. For those who were given the treatment text, we find that 91.3% of students answered "yes" when asked if found the information useful. In contrast, for those students given the control text, when asked if they would like to learn about participating in research, only 49.6% of students answered "yes". We see this as evidence that students not only read the treatment information provided to them carefully, but that broadly speaking they found it beneficial and were poised to incorporate it into their behavior.

5.2 Experimental Results

To study the effects of the information treatment on our outcomes of interest, we estimate the following statistical model

$$y_i = \alpha + \beta TREAT_i + PT_i\gamma + X_i\phi + B_i\lambda + \psi + \epsilon_i$$

where y_i is an outcome of interest (eg. time spent on homework), PT_i (pre-treatment) is a vector containing exam one and homework one scores, and X_i is a vector of demographic characteristics including gender, race/ethnicity indicators, an indicator for whether the student is socio-economically disadvantaged as well as an indicator for first-generation status. We also include responses from the baseline survey, found in B_i, that capture important beliefs about choice of major, ability in economics, expected grade in the course, as well as beliefs about typically study habits and beliefs about returns to study effort. We control for section fixed effects with ψ. Lastly, ϵ_i represents a random error term. The $TREAT_i$ variable represents assignment to the treatment group. Random assignment to the treatment group ensures that $corr(TREAT_i, \epsilon_i) = 0$, allowing us to estimate the causal effect of the information treatment on our outcomes of interest[5].

Our primary outcome of interest is time spent on homework assignments that were due after exam one, when treatment was assigned, and exam two. This time period corresponds to homeworks two, three, four and five.

We take time spent on these homeworks to be the most valid measurement of study effort in our setting, for multiple reasons; first, outside of exams, there were no other activities other than homeworks for which the students could receive course credit; second, this would be the time of the course, just after receiving the information about returns to study effort, students would be mostly likely to remember the information and incorporate it into their studying decisions; third, after this set of homeworks and subsequent exams, students will have received new signals about the returns to their study effort that may or may not lead them to update their beliefs about the relationship between that effort and achievement; lastly, time spent studying is the variable over which students have the most control, while other outcomes such as scores on homeworks and exams are the result of a mapping of that effort onto an achievement. We present analyses focusing on these other outcomes as well, although for these reasons, we believe the most valid outcome for

[5] Under random assignment, treatment status is uncorrelated with observable characteristics. Our treatment balance analysis in section 5.1 confirms this is true for our setting

our purposes is study time on homeworks two through five.

We take the log of total time spent on these homeworks in order to approximate a percentage change in study time as a result of treatment. Results from our principal analyses looking at study time, as well as homework, exam and overall course performance can be found in table 4. Focusing first on the effect of the intervention on time spent on homework two, we see that under our baseline specification, which controls for performance on exam one as well as log study time on homework one and section fixed effects, the treatment caused a 26% increase in study effort. This result is significant at the 5% level.

Under our controls specification, which along with those variables mentioned in baseline specification also controls for demographics and baseline survey responses, the effect size decreases slightly but remains mostly stable, dropping to 23% (significant at 10% level). We see this as strong evidence that those who received information about returns to studying significantly increased their study effort in the period directly after the intervention.

We also see positive effects on time spent on homework when extending our outcome to homeworks two through five and two through nine, although the treatment effect does decrease in magnitude. We will discuss what may be driving this result when we go over our results based on beliefs about returns to study effort. Looking at homework scores, we also find positive and significant effects across all sets of homeworks[6].

We also study the effect of treatment on exam and overall course performance. For reasons similar to those regarding homework scores, our preferred measures of exam performance are percentage score on exam two (0 - 100 scale), as well as median percentage score on exams two through four (i.e. those after exam one, all which took place after the treatment was administered) [7].

For overall course performance, we take percentage points of total grade as our main outcome. Results for these outcomes can be found in Panel C of table 4. Looking at the results on exam performance, we see that the treatment had little effect. This is surprising, given the large treatment

[6] When considering multiple homeworks, as is the case when estimating the treatment effect on scores on homeworks two through five or two through nine, our preferred measure of homework scores is median homework score. We take this approach for a specific reason. As part of the course design, along with their lowest exam score, each student's lowest homework scores is automatically dropped from their final course point total.

[7] Along with dropping their lowest homework score, students' lowest exam score was also dropped from their total course points total.

effects found in both study time and score for homeworks two through five. Our estimates for overall course performance are between 6% and 8.8% of a standard deviation in that outcome, although these results lack statistical significance. Again, we consider why this may be the case when we study the role of beliefs.

As mentioned earlier, our baseline survey asked student "How many hours would you need to study each week to increase your grade by one letter in this course?". This provides us with a measure of students' beliefs about the returns to their study effort in this course. We explore the possibility of heterogeneous impacts across beliefs about returns to study effort by replacing our treatment variable with two indicators each representing whether a student's beliefs about returns to study effort was above or below the three and a half hours contained in our information treatment, each interacted with treatment status. Connecting back to our framework in section 2, interpreting the signs of the coefficients on homework time will tell us whether the income or substitution effect dominates as students update their study effort upon receiving information about its returns.

Focusing on the effect on time on homework two, we find large effects, both in magnitude and in significance for those who originally over-estimated their returns to study effort. The treatment managed to increase study effort by between 62 and 68% for these students. While the coefficient for those who originally under-estimated the returns is positive and large, it is less than a third of the effect for those who over-estimated returns and is not statistically significant at conventional levels.

The pattern completely flips when looking at effort throughout the course. Those who initially overestimated returns now have no or even a negative treatment effect, while those who underestimated increased their effort by 10% throughout the course. We see similar effects when looking at homework scores, although the coefficients for these two groups are virtually identical when looking at scores throughout the course (homeworks 2-9).

These results are consistent with a story in which students who originally underestimated returns to study effort substitute *into* studying after learning that academic achievement is *cheaper*. For these students, this implies that the substitution effect dominates the income effect, which would mean less studying, in this case. Interpreting the results for those who originally over-estimated returns is a bit less clear as the initial surge in study effort would signify a strong income effect, as students study more upon learning they are *richer* in achievement. We see that these effects do not persist throughout the course, however, and the effect on study effort is even negative when controlling for demographics and beliefs, implying a substitution *out of* studying for the course as a whole.

Looking at exam and course performance, the treatment effect on median exam score for those who underestimated is to 0.026 percentage points, which correspond to an increase of 25% of a standard deviation in median exam performance and is significant at the 5% level. We estimate negative treatment effects for those who originally over-estimated returns to study effort of -3.3 and -4.3 points in our baseline and controls specifications respectively, although neither are statistically significant.

We also estimate a statistically significant treatment effect on overall course performance of 1.5 percentage points in our controls specification for those under estimated returns to study effort. This represents 16% of a standard deviation in course performance. We find a negative treatment effect for those who over-estimate returns of between -0.40 and -0.98, although these results are noisier than for those who under-estimated returns.

We estimate similar models looking at both low and high income students. These results can be found in table 7. While we see a large and significant treatment effect for low-income students on time spent on homeworks, with a 26% increase in study effort throughout the course, we find no treatment effect on median homework scores for this group. Similar to the pattern found in our study of beliefs, we see large and significant effects for high-income students on homework score, but effects on homework time are noisy and remain smaller than those for low-income students.

In stark contrast to our results for the full sample, we see large positive treatment effects on exam and course performance for low-income students. Looking at performance on all exams, we see that our treatment increased median test score by 0.024 to 0.040 percentage points in our baseline and control specifications respectively, with the latter just outside the 10% significance level (p-value = 0.016). We also see large effects on course performance, although these results also lack statistical significance.

6 Conclusion and Discussion

In this paper, we study the effect of providing students with information about returns to study effort. We measure the impact of receiving this information on several important outcomes such as study effort, homework and exam performance as well as overall course performance. We are able to measure study effort using an extremely granular data source based on time-use data from the course's online homework software.

We find that our treatment led to a significant increase in study effort as well as homework performance. Along with these results, we also find interesting results based on initial beliefs about returns to study effort. Specifically, we find that those who had originally under-estimated the returns to study effort studied more throughout the course compared to the control group with large and significant gains on exam and overall course performance.

Those who had originally over-estimated returns to study effort increased their study effort greatly directly after the intervention, but in contrast to those who had under-estimated, this effect disappears when measuring effort throughout the course. We find that these long term effects on study effort for those who under-estimated translate into significant increases in exam performance as well as course performance.

We also find large and persistent effects on study effort for low income students, with suggestive evidence on exam and course performance for this subgroup.

We find that our results are consistent with a story where students who originally underestimated returns to study effort substituted into studying more for the class upon receiving information, while those who originally over-estimated did not and may have even studies less. This points to a dominant substitution effect as students learn about the returns to study effort.

Our results are important for policy makers who wish to increase achievement and persistence in college for many reasons. Firstly, we document that the vast majority of students in our study under-estimate the returns to study effort. Our experimental results show that these students are likely to increase their study effort upon learning true returns to their effort. Depending on the distribution of beliefs within different classrooms, however, there may be unintended consequences as students with high beliefs of returns to study effort may not study more or may even study less.

Policy makers should be aware of this potential trade-off.

Our results also show that providing students with information about previous cohorts studying patterns may provide large gains in achievement at a low cost. Compared to other studies aiming to increase achievement, our results on course performance compare favorably.

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7 Tables and Figures

Table 1: Difference of means between treatment and control (demographics)

	(1)
female	-0.0205
	(-0.36)
Low Income	0.0165
	(0.33)
African American	-0.00464
	(-0.24)
White	0.0406
	(0.86)
Hispanic	-0.0516
	(-1.09)
Asian	-0.00615
	(-0.11)
sat_act	0.293
	(0.01)
First Generation	-0.0484
	(-0.87)
Observations	304

t statistics in parentheses

Data are from main analysis sample.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Difference of means between treatment and control (beliefs and academics)

	(1)
Q9	-1.210**
	(-2.04)
Q8	0.0553
	(0.12)
econ_top	-0.0731
	(-1.41)
econ_ab_high	-0.00234
	(-0.05)
econ_ab_mid	-0.0162
	(-0.30)
exp_grade_a	0.171***
	(3.01)
exp_grade_b	-0.123**
	(-2.18)
exp_grade_c	-0.0123
	(-0.94)
high_control	0.0511
	(1.07)
Exam 1	1.162
	(0.56)
HW 1 time	-0.0286
	(-0.40)
Observations	304

t statistics in parentheses

Data are from main analysis sample.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Predictors of beliefs of returns to study effort

	(1)
	Q9
female	0.361
	(0.85)
Low Income	0.386
	(0.66)
African American	-0.695
	(-0.39)
White	0.284
	(0.20)
Hispanic	-0.128
	(-0.09)
Asian	-0.0914
	(-0.07)
sat_act	-0.000311
	(-0.23)
First Generation	-0.294
	(-0.55)
transfer	0.838
	(0.41)
Q8	0.647***
	(12.34)
econ_top	0.102
	(0.21)
high_control	-14.19***
	(-6.36)
mid_control	-13.45***
	(-5.95)
low_control	-12.88***
	(-4.23)
exp_grade_a	0.115
	(0.13)
exp_grade_b	0.349
	(0.40)
exp_grade_c	3.972**
	(2.36)
econ_ab_high	-1.120
	(-0.54)

Table 4: The effect of treatment on homework time and scores, as well as exam and course performance

Panel A: Effects on Time Spent on Homeworks						
	(1) HW 2 time	(2) HW 2 time	(3) HW 2-5 time	(4) HW 2-5 time	(5) HW 2-9 time	(6) HW 2-9 time
TREAT	0.264**	0.232*	0.110**	0.124**	0.0670	0.0768
	(0.128)	(0.128)	(0.0543)	(0.0575)	(0.0523)	(0.0557)
Panel B: Effects on Scores on Homeworks						
	(7) HW 2 score	(8) HW 2 score	(9) Median HW score (2-5)	(10) Median HW score (2-5)	(11) Median HW score (2-9)	(12) Median HW score (2-9)
TREAT	0.0665**	0.0565*	0.0403**	0.0442**	0.0222	0.0313*
	(0.0288)	(0.0294)	(0.0189)	(0.0199)	(0.0183)	(0.0183)
Panel C: Effects on Exams And Course Performance						
	(13) Exam 2 Score	(14) Exam 2 Score	(15) Median exam Score (2-4)	(16) Median exam Score (2-4)	(17) Pct Total Course Pts	(18) Pct Total Course Pts
TREAT	0.00329	0.0044	0.00915	0.0170	0.639	1.115
	(0.0147)	(0.0157)	(0.0111)	(0.0118)	(0.666)	(0.677)
Observations	304	304	304	304	304	304
Baseline	x	x	x	x	x	x
Controls		x		x		x

Robust standard errors in parentheses

Note:

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Heterogeneous effects by beliefs of treatment on homework, exam and course outcomes

Panel A: Effects on Time Spent on Homeworks						
	(1) HW 2 time	(2) HW 2 time	(3) HW 2-5 time	(4) HW 2-5 time	(5) HW 2-9 time	(6) HW 2-9 time
Over Estimate Returns	0.684***	0.617**	0.129	0.103	0.000500	-0.02723
	(0.237)	(0.252)	(0.112)	(0.119)	(0.106)	(0.106)
Under Estimate Returns	0.196	0.145	0.107*	0.128**	0.0778	0.100*
	(0.134)	(0.136)	(0.0563)	(0.0605)	(0.0545)	(0.0592)
Panel B: Effects on Scores on Homeworks						
	(7) HW 2 score	(8) HW 2 score	(9) Median HW score (2-5)	(10) Median HW score (2-5)	(11) Median HW score (2-9)	(12) Median HW score (2-9)
Over Estimate Returns	0.207***	0.172***	0.114***	0.0850**	0.0528	0.0362
	(0.0591)	(0.0415)	(0.0435)	(0.0432)	(0.0425)	(0.0439)
Under Estimate Returns	0.0414	0.032	0.0239	0.0350	0.0129	0.0302
	(0.0323)	(0.0346)	(0.0239)	(0.0258)	(0.0235)	(0.0248)
Panel C: Effects on Exams And Course Performance						
	(13) Exam 2 Score	(14) Exam 2 Score	(15) Median exam Score (2-4)	(16) Median exam Score (2-4)	(17) Pct Total Course Pts	(18) Pct Total Course Pts
Over Estimate Returns	-0.0421	-0.0379	-0.0218	-0.0239	-0.403	-0.805
	(0.0334)	(0.0350)	(0.0219)	(0.0224)	(1.494)	(1.401)
Under Estimate Returns	0.0107	0.0140	0.0142	0.0263**	0.808	1.551**
	(0.0148)	(0.0166)	(0.0115)	(0.0126)	(0.681)	(0.731)
Observations	304	304	304	304	304	304
Baseline	x	x	x	x	x	x
Controls		x		x		x

Robust standard errors in parentheses

Note:

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Heterogeneous effects by low and high income status of treatment on homework, exam and course outcomes

Panel A: Effects on Time Spent on Homeworks						
	(1) HW 2 time	(2) HW 2 time	(3) HW 2-5 time	(4) HW 2-5 time	(5) HW 2-9 time	(6) HW 2-9 time
Low Income (Treat)	0.462*	0.515*	0.291***	0.331***	0.245**	0.262**
	(0.276)	(0.285)	(0.109)	(0.114)	(0.106)	(0.112)
High Income (Treat)	0.199	0.138	0.0516	0.0546	0.0101	0.0153
	(0.148)	(0.148)	(0.0603)	(0.0648)	(0.0587)	(0.025)
Panel B: Effects on Scores on Homeworks						
	(7) HW 2 score	(8) HW 2 score	(9) Median HW score (2-5)	(10) Median HW score (2-5)	(11) Median HW score (2-9)	(12) Median HW score (2-9)
Low Income (Treat)	0.00276	0.00175	0.0340	0.0491	0.0207	0.0333
	(0.0602)	(0.0604)	(0.0373)	(0.0384)	(0.0360)	(0.0361)
High Income (Treat)	0.0878***	0.0749**	0.0430**	0.0426*	0.0237	0.0308
	(0.0329)	(0.0344)	(0.0216)	(0.0222)	(0.0210)	(0.0212)
Panel C: Effects on Exams And Course Performance						
	(13) Exam 2 Score	(14) Exam 2 Score	(15) Median exam Score (2-4)	(16) Median exam Score (2-4)	(17) Pct Total Course Pts	(18) Pct Total Course Pts
Low Income (Treat)	0.0286	0.0388	0.0235	0.0402	0.965	2.032
	(0.0348)	(0.0358)	(0.0253)	(0.0248)	(1.539)	(1.444)
High Income (Treat)	-0.00586	-0.00701	0.00427	0.00929	0.522	0.810
	(0.0158)	(0.0161)	(0.0126)	(0.0132)	(0.733)	(0.768)
Observations	304	304	304	304	304	304
Baseline	x	x	x	x	x	x
Controls		x		x		x

Robust standard errors in parentheses

Note:

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A Appendix

A.1 Treatment and Control Information

Treatment text

Benefits of Study Effort

Recent research has demonstrated that students underestimate the benefits of study effort

Using data from Prof. Carrell's course last year, we found a significant relationship between the time students spent on homework and their course grade.

Specifically, we found that for the average student **an additional three and a half hours of study time per week** was associated with an improvement of a **full letter grade for the course.**

Control Text

Benefits of Research Participation

Student participation in research is an integral part of the research process here at UC Davis

As social science research continues to study how people make important decisions, students have been asked to dedicate more of their time to research participation. There are many benefits of research participation in general, including learning how research is conducted.

We hope you have found your participation in this project to be interesting.