Microcommitments: The Effect of Small Commitments on Student Success

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I. Motivation

Higher education is in a unique position to enhance social mobility, mitigate inequality and affect positive change on the world's economic and social landscape. Since the labor market continues to reward those who remain in school longer, investing in human capital among the less advantaged is key to mitigating swelling inequality (Becker and Murphy 2007; Haskins et al. 2009). Matriculation rates indicate there has been a rise in opportunities for traditionally underrepresented groups (TUGs) in higher education. Yet commencement statistics demonstrate little change in who earns degrees.

Because students from TUGs enter college with different habits and networks, they may be less prepared to be successful. For instance, first generation college students (who are disproportionately from TUGs) may not grow up watching their parents make lists, prioritize and manage time in a way that would promote college success. This means that, even if applied symmetrically across all students, student success efforts can have a higher marginal impact on those from TUGs in higher education, which could mitigate economic and social inequality.

Recent studies have shown that students' social networks matter to their success, and this is particularly true for low-income students, who are disproportionately from TUGs. Studies examining the success of low-income students find nonfinancial support from their families significantly affect their academic outcomes, and appropriate emotional support facilitates

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psychological wellbeing, enhancing student engagement (Roksa and Kinsley 2019). Arguably, families of low-income students may be less able to provide the type of support necessary to support student success, making it more important for institutions to evolve in ways that foster this success and ensure inclusivity in higher education.

The findings that students from TUGs are academically and personally underprepared for the challenges of college are compounded by the fact that students from backgrounds of low socioeconomic status disproportionately enroll in online courses. While online courses provide students with increased flexibility and access to education, they are found to be less effective along myriad measures of academic success (Bettinger et al. 2017). This is evidence that as we seek to develop interventions to bolster student performance, particularly for those with the most need, we must focus on online and hybrid modalities to effectively mitigate economic inequality.

II. Behavioral Change, Student Characteristics and Course Modality

Behavioral economists know that time inconsistent preferences leave room for welfare enhancing behavioral interventions. Individuals have a tendency to procrastinate onerous tasks and this is especially salient among undergraduate students. Not only do time inconsistent preferences theoretically affect student performance, there is empirical evidence that procrastination adversely affects student performance (see Kim and Seo 2015, for a meta-analysis of 33 relevant studies with over 38,000 participants).

Theoretically, commitment devices can mitigate procrastination by increasing the costs of putting off tasks, thereby inducing individuals to adapt behavior that is time inconsistent. Several empirical studies have shown the effectiveness of commitment devices in realms where individuals often procrastinate and suffer the consequences of inaction. Researchers have designed effective commitment devices to induce exercise (Royer et al. 2015), increase saving

(Gugerty 2007) and even to quit smoking (Giné et al. 2010). One way to make a commitment device effective is to introduce social accountability, whereby increasing the cost of not following through increases the likelihood that the commitment leads to action. This effect has been shown most starkly in saving behavior in developing countries (Gugerty 2007).

While research on behavioral change in the realm of student success is limited, there are a few notable studies. In a Stanford University MOOC, researchers found that commitment devices with reminders induced students to devote 24% more time to their coursework, yielding higher grades and completion rates (Patterson 2015). Ariely and Wertenbroch (2002) found that students who are self-aware of their procrastination habits chose to commit to intermediate course deadlines, which led to improved performance. Finally, several studies have measured the effect of nudging college students to engage with course content via text messages and providing coaching tips (e.g., Oreopoulos et al. 2020, 2019, 2018). These studies found that mere nudges do not significantly affect student academic performance. But when nudges are targeted to a particular group of students with clear implications acting as an incentive (e.g., a change in course grade), the nudges are effective (Chen and Okediji 2014, Main and Griffith 2019, Smith et al. 2018). Our student intervention goes beyond nudging and creates an environment with commitment devices and social accountability geared toward enhancing student performance.

III. The Intervention

To determine whether economics content delivered with commitment devices accompanied by social accountability can enhance student performance, we conducted a randomized controlled experiment in Fall 2019. Experiment participants were recruited from economics courses taught by six instructors, at three universities, using three teaching modalities—face-to-face, online and hybrid.

After providing demographic and behavioral information, students were randomly assigned to the control or treatment group. Between two exams in their courses, all participating students were sent daily content that corresponded to the material they were learning in their course. The content was designed to engage students for no more than five minutes per day. These small actions included problems, prompts to practice important concepts and questions compelling students to relate course material to their own lives. No problems or answers were turned in by students or reviewed by instructors. All content was delivered via text message every morning accompanied by a picture and quote. Depending on the timing of the bookending exams, students received the experiment's content for approximately three weeks.

All students received the same daily content. Those in the control group received the content via MMS, nudging them to do the small task. Students in the treatment group received the content from a platform accessed via a link sent by SMS containing the same daily task but with a commitment device called a microcommitment. These students are asked whether they commit to doing the task that day. If they commit, the platform would follow up in the late afternoon and ask whether they did the task. The appendix shows the experience. Commitments and completed tasks appear on a social feed that provides some social accountability.

IV. Empirical Model, Measurement and Descriptive Statistics

To isolate the effect of microcommitments on student performance, we employ regression analyses using the following empirical model for student performance: $P_{ic} = \alpha + \beta M_{ic} + \partial X_{ic} + \gamma_c + u_{ic}$. This equation indicates that the performance (*P*) of student (i) in course (c) is a function of whether or not the student received economics content with the opportunity to make microcommitments (*M*) as well as the student's demographic and self-reported behavioral characteristics (vector *X*). The model also includes course level fixed effects

(γ) to control for systematic, yet unobservable, differences between instructors and across sections of the course. Finally, u is a randomly distributed error term.

To further account for variation across instructors and classes, performance is measured with relative exam scores, defined as the student's percentage grade minus the average percentage grade as a proportion of the class's average percentage grade. Specifically, we consider the relative score earned by the student during the exam immediately following the intervention and control for their relative performance on the exam preceding the intervention. Students were randomly assigned to each group, so there should be no correlation between receiving microcommitments and individual characteristics. Thus, the basic specification measures the effect of receiving microcommitments controlling only for previous exam score and class fixed effects. The second specification controls for age, gender, race, financial aid status, whether the course is required, past performance and current study habits. The latter specification provides a robustness check in case the random assignment yielded significantly different groups of students. Table 1 defines these variables and provides descriptive statistics.

[Table 1 here]

This analysis focuses on procrastination and self-efficacy, two potentially important components of student success. To measure procrastination, the initial survey completed by student participants includes several questions from those that comprise the Irrational Procrastination Scale (IPS) (Steel 2010). The IPS measures self-perceptions of procrastination and irrational delays in completing tasks. Students with higher than average procrastination measures are categorized in the high procrastination category. Similarly, we create a high self-efficacy measure from the self-efficacy questions on the Motivation Styles and Learning Questionnaire (Pintrich et al. 1991) and categorize students as high relative to the mean.

V. Results

An ordinary least squares (OLS) analysis finds that microcommitments have a positive and significant effect on student performance. The coefficients in Tables 2 and 3 represent the impact of a one-unit change in the independent variable on the relative performance during the exam following the intervention as a proportion of the average exam score. As a proportion of the class average, relative performance increases significantly by 0.015 to 0.017, or approximately 1.3 additional percentage points on the post-intervention exam for those in the treatment group. The positive effect of microcommitments is driven by improved performance among students in online and hybrid courses, and is equivalent to approximately 3.5 additional percentage points on the post-intervention exam. The effect of microcommitments with social accountability on students in face-to-face courses is insignificant. Perhaps this intervention with commitment devices and social accountability partially substitutes for the lack of instructor contact when a course is taught in an online or hybrid modality. Alternatively, there may be spillover effects between groups as face-to-face students are more likely to talk to one another.

[Table 2 here]

The results in Table 3 describe in more detail the effects of the intervention on student success in online and hybrid courses. The analysis considers how the effect may systematically differ according to student characteristics and behaviors. Specifically, results are reported by previous performance, procrastination type and self-efficacy. Notably, microcommitments affect positively and significantly students with inferior previous academic performance as measured by reported GPA. This means microcommitments with social accountability are an equalizing force in terms of academic performance. This could have positive implications for social mobility and, at a large enough scale, enhance economic equity.

[Table 3 here]

While microcommitments positively impact the performance of both high and low procrastination types, the marginal effect for high type procrastinators is 40% larger in the first specification. This finding could be illuminating the mechanism through which commitments and social accountability enhance student performance, such as mitigating procrastination in online and hybrid classes. While we would most like to reach students with the lowest self-efficacy with performance-enhancing interventions, microcommitments do not have a significant effect on performance among these students. However, they do positively affect performance among students with above average self-efficacy. This finding is consistent with research linking higher levels of self-efficacy to behavioral improvement (Bandura and Adams 1977).

VI. Conclusion and Implications

This paper presents evidence that microcommitments with accountability can serve as a substitute for the accountability provided by in-person interactions with instructors. They could be used to mitigate the lower levels of academic performance often seen in online learning environments. At the institutional level, microcommitments and social accountability could help navigate some of the tradeoffs institutions face when transitioning from face-to-face to online courses, especially in the wake of the COVID-19 pandemic.

Insofar as microcommitments asymmetrically affect students, and marginally impact those who need help the most, they can have a positive impact on social mobility and equity. Furthermore, if the commitments with accountability are mitigating procrastination and helping students acquire more successful behaviors, then they will have the greatest impact on those who are the first in the family to attend college. This will make higher education more inclusive and help combat growing economic inequality.

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Table 1. Variable Definitions and Descriptive Statistics By Course Type

	Definition	**Total** Mean (Std. Dev)	**Face-To-Face Courses** Mean (Std. Dev)	**Online and Hybrid Courses** Mean (Std. Dev)
Dependent Variables				
Exam After	Score on exam immediately following experiment, percentage	81.14 (13.36)	82.35 (10.91)	79.10 (16.53)
Relative Exam After	(Student Exam After Score – Class Mean Exam After)/Class Mean Exam After	0.010 (0.154)	0.010 (0.131)	0.009 (0.186)
Explanatory Variables				
Microcommitments	=1 if the student was offered microcommitments with social accountability	0.532 (0.499)	0.530 (0.500)	0.535 (0.499)
Exam Before	Percentage score on exam before the experiment	85.41 (12.42)	87.15 (10.11)	82.46 (15.15)
Relative Exam Before	(Student Exam Before Score – Class Mean Exam Before)/Class Mean Exam Before	0.002 (0.138)	0.000 (0.112)	0.006 (0.174)
Prior Econ	=1 if has taken a college-level micro- or macroeconomic principles course in a prior semester	0.279 (0.449)	0.300 (0.459)	0.243 (0.429)
High Perform	=1 if prior GPA > 3.75 or SAT score > 1450 or ACT score > 32	0.571 (0.495)	0.777 (0.416)	0.222 (0.416)
Required	=1 if the course is required for major	0.769 (0.422)	0.748 (0.434)	0.804 (0.398)
High Study Hours	=1 if student studies at least 7 hours per week	0.095 (0.294)	0.105 (0.306)	0.079 (0.271)
Female	=1 if female	0.468 (0.499)	0.421 (0.494)	0.549 (0.498)
Nonwhite	=1 if nonwhite	0.304 (0.460)	0.212 (0.409)	0.460 (0.499)
Financial Aid	=1 if student receives financial aid	0.389 (0.488)	0.366 (0.482)	0.428 (0.495)
High Efficacy Type	=1 the student's responses to the MSLQ self-efficacy questions were above average	0.566 (0.496)	0.550 (0.498)	0.593 (0.492)
High Procrastination	=1 if the student's IPS responses were above the participant average	0.517 (0.500)	0.477 (0.500)	0.584 (0.493)

Table 2. Relative Student Performance By Class Type

	Dependent Variable							
	Relative Exam After							
	Total		Face-To-Face		Hybrid		Online	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Microcommitments	0.017**	0.015**	0.001	-0.001	0.032*	0.040**	0.054***	0.044**
	(0.008)	(0.008)	(0.009)	(0.009)	(0.019)	(0.019)	(0.021)	(0.021)
Exam Before	0.576***	0.526***	0.535***	0.469***	0.690***	0.667***	0.614***	0.559***
	(0.028)	(0.029)	(0.038)	(0.042)	(0.124)	(0.129)	(0.049)	(0.052)
Prior Econ		-0.003		-0.001		-0.002		-0.005
		(0.010)		(0.011)		(0.034)		(0.022)
High Perform		0.042***		0.046***		0.027		0.064**
		(0.010)		(0.011)		(0.022)		(0.022)
Required		0.029***		-0.021**		-0.044**		-0.068**
		(0.009)		(0.010)		(0.021)		(0.033)
High Study Hours		-0.004		-0.010		-0.064		0.014
		(0.013)		(0.014)		(0.049)		(0.034)
Female		0.0004		-0.006		0.034*		-0.014
		(0.008)		(0.009)		(0.019)		(0.021)
Nonwhite		-0.002		0.012		-0.049**		-0.008
		(0.009)		(0.011)		(0.020)		(0.021)
Financial Aid		-0.020**		-0.014		0.005		-0.040*
		(0.008)		(0.009)		(0.021)		(0.021)
Adjusted R^2	0.276	0.296	0.230	0.250	0.180	0.211	0.358	0.385
Sample Size	1155	1155	727	727	152	152	276	276

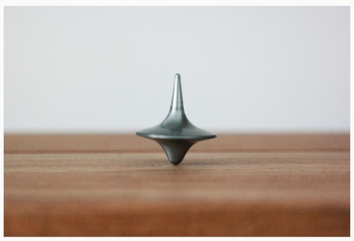
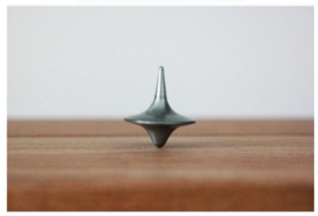
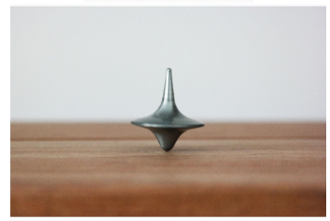
*Standard errors are in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively*

Table 3. Online and Hybrid Student Performance By GPA, Procrastination and Self-Efficacy

	Dependent Variable							
	Relative Exam After							
	By Procrastination				By Self-Efficacy			
	High	High	Low	Low	High	High	Low	Low
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Microcommitments	0.052***	0.051**	0.037*	0.048**	0.051***	0.051***	0.034	0.032
	(0.020)	(0.020)	(0.022)	(0.022)	(0.019)	(0.018)	(0.025)	(0.025)
Exam Before	0.568***	0.549***	0.675***	0.602***	0.669***	0.625***	0.479***	0.449***
	(0.059)	(0.061)	(0.062)	(0.064)	(0.054)	(0.056)	(0.072)	(0.074)
Prior Econ		-0.020		0.024		-0.026		0.038
		(0.024)		(0.027)		(0.022)		(0.031)
High Perform		0.029		0.061**		0.046**		0.024
		(0.026)		(0.027)		(0.022)		(0.035)
Required		-0.048*		-0.057*		-0.053**		-0.046
		(0.026)		(0.034)		(0.025)		(0.032)
High Study Hours		-0.012		0.016		-0.021		0.055
		(0.044)		(0.035)		(0.032)		(0.053)
Female		0.007		0.003		-0.010		0.047*
		(0.021)		(0.022)		(0.019)		(0.026)
Nonwhite		-0.002		-0.056**		-0.022		-0.030
		(0.021)		(0.023)		(0.019)		(0.024)
Financial Aid		-0.013		-0.038*		-0.012		-0.039
		(0.021)		(0.025)		(0.020)		(0.025)
Adjusted R^2	0.278	0.248	0.395	0.441	0.389	0.411	0.201	0.218
Sample Size	250	250	178	178	254	254	174	174

*Standard errors are in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively*

Appendix 1. Control and Treatment Experience

Control Group	**Treatment Group**	
Content delivered via MMS every weekday morning at 9am.	A link to the content is delivered via SMS twice a day. In the morning it includes an "I commit" button and in the afternoon, it includes an "I did it" button.	
	Commitment Device	
484848	**9am**	**4pm**
	Today's Activity-Production 3: http://prohab.it/kl1sxf4	Did you do it?-Production 3: http://prohab.it/aun5hy3
Production 3 10:00 AM, Oct 23  SAVE "Knowledge is the only instrument of production that is not subject to diminishing returns." ~ John Maurice Clark The Law of Diminishing Returns states that a decrease in output can be observed if a single input is increased over time. Think about how this relates to your studying. As you begin studying for an exam, how much new information do you absorb in the first hour? The second hour? The tenth hour? The twentieth hour?	Production 3  "Knowledge is the only instrument of production that is not subject to diminishing returns." ~ John Maurice Clark The Law of Diminishing Returns states that a decrease in output can be observed if a single input is increased over time. Think about how this relates to your studying. As you begin studying for an exam, how much new information do you absorb in the first hour? The second hour? The tenth hour? The twentieth hour? I Commit	Production 3  "Knowledge is the only instrument of production that is not subject to diminishing returns." ~ John Maurice Clark The Law of Diminishing Returns states that a decrease in output can be observed if a single input is increased over time. Think about how this relates to your studying. As you begin studying for an exam, how much new information do you absorb in the first hour? The second hour? The tenth hour? The twentieth hour? I did it