Nudging in Higher Education: Text Message Interventions and Study Habits in Mathematics

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Abstract. In this field experiment, we explore the connection between study habits and academic achievement among undergraduates in an introductory mathematics course at a Norwegian college. Using a procrastination scale based on self-reported behavior, we examine how students' study habits influence their performance. Our findings reveal a negative correlation between self-identified procrastinators and the number of problem-sets submitted. Moreover, there is significant correlation between procrastination tendencies and the final course grade, but only for two of the four dimensions we use to measure procrastination. Notably, 43% of the variation in the final grade can be accounted for by prior competence, number of homework's and the student's age. Furthermore, to establish causality, we randomly divided the students into two groups: one received a text message on their mobile devices and the other did not. The text message emphasized the positive link between the number of completed problem sets and improved academic performance in the final exam. Through this controlled approach, we assess the impact of the text message on problem set submission and final exam performance. Our results indicate that the text message exerts no discernible influence on either the quantity of problem sets submitted or the performance in the final exam.

Keywords: Higher Education, Field Experiment, Procrastination, Mathematics.

1 Introduction

Mathematics, particularly mathematical analysis, plays a pivotal role in various disciplines such as engineering, data science, and economics. Students must cultivate analytical thinking, mathematical proficiency, fluency, and problem-solving skills to excel in their respective fields. Achieving these competencies requires significant dedication and time investment. Furthermore, advanced courses within these programs utilize mathematics to comprehend natural and societal phenomena, underscoring the importance of strong mathematical performance for future academic development in related subjects. Those familiar with students recognize that they often do not maintain a steady pace of work throughout the semester, failing to allocate sufficient time for material comprehension. This tendency to delay work can be characterized as procrastination, where individuals postpone tasks, they find unpleasant, wishing to complete them sooner [1]. Nevertheless, anecdotal evidence suggests that students who consistently engage with course material during the semester, actively participating in exercise seminars and submitting problem sets promptly, tend to achieve better results. However, it remains uncertain whether their performance surpasses that of students who do not maintain this consistent approach. A deeper understanding of the relationship between students' activity over time and their academic performance can shed light on the factors contributing to poor academic outcomes and dropout rates.

In a randomized experiment conducted by Clark, Gill [2], students were assigned various types of goals, which could be categorized as task-based or goal-based. Notably, students provided with task-based goals exhibited an increase in the number of practice problems submitted, and this effect extended to improvements in their final exam performance. In contrast, Oreopoulos and Petronijevic [1] found no significant impact on academic performance resulting from different low-threshold goal-setting interventions among a sizable sample of 25,000 undergraduate students in Canada. They proposed that these interventions may yield limited learning gains due to inadequate student time investment in their studies. One potential explanation for the divergent findings is that interventions may be more effective for students prone to procrastination, but when applied to larger, more diverse student populations, the effects tend to average out. Importantly, previous studies have not considered students' study habits, which could further influence the outcomes.

This paper attempts to addresses two primary questions: (i) do students who self-identify as non-procrastinators submit more exercises and achieve better academic results compared to students who identify as procrastinators? (ii) what is the causal effect of a low threshold intervention, specifically a text message follow-up, on the number of problem-sets submitted and academic performance in the final exam?

Our study relies on students' self-reported study habits, gauged through a set of questions developed in psychometrics designed to measure their propensity to procrastinate. These psychometric scales were developed by Svartdal [3] and Choi and Moran [4] and encompasses various dimensions of procrastination. We then randomly allocate half of the students to receive a low-threshold intervention in the form of text messages, while the other half remains without intervention. This randomization enables us to establish a causal link between the intervention and both problem-set submissions and academic performance. Our contribution to the literature on low-threshold interventions lies in our investigation of student responses within a small-scale experiment. We further enhance our analysis by controlling for student habits, using self-reported psychometric scales. This control allows us to discern potential variations in the impact of low-threshold interventions based on distinct study habits.

The remainder of the paper is organized as follows. First, we introduce academic procrastination and related studies on low-threshold follow-up interventions or nudges. Second, we present the experimental design and data collection. Next, we present the preliminary findings and finally conclude and reveal our future research direction.

2 Related Work

Academic procrastination is an increasing concern within the educational sector, especially in this pandemic [5-7]. According to recent study by Melgaard, Monir [7] "prior studies have found that low self-efficacy, disorganisation, low intrinsic motivation, poor effort regulation, and time management are all strong characteristics of academic procrastination [8-12], and thus, argue that academic procrastination is a reliable predictor of poor academic performance [11, 13, 14]". Nudging is a concept developed by behavioral economists and psychologists, and is broadly understood as an simple intervention that alters people behavior in a predictable way while preserving a full freedom of choice [15, 16]. Nudges are mostly "simple, inexpensive psychological supports that appeal to reflective thinking and thus stimulate more rational decision making" [17]. While types of nudging spans an wide range; in this study we primarily employ; a) uses of social norms, b) reminders, and c) eliciting implementation intentions as described by Sunstein [16]. In this study we employ "reminders" as a mobile text message (SMS) follow-up.

The existing literature on these low-threshold follow-up interventions or nudges has yielded varied outcomes. On one hand, some studies have reported enhanced student performance when external deadlines or follow-up mechanisms are employed. For instance, Ariely and Wertenbroch [18] examined student performance across three proofreading tasks over a 21-day period, comparing conditions with and without deadlines. The results revealed that students subjected to evenly spaced deadlines significantly outperformed those without any intermediate deadlines as compared those with self-set intermediate deadlines. This difference was attributed to a potential lack of awareness or understanding of self-control issues among students. Similarly, Himmler, Jäckle [19] employed non-binding agreements and observed that students were more likely to enroll in courses, participate actively, and achieve passing grades. Notably, the commitment device appeared to be most beneficial for students characterized as procrastinators.

On the other hand, some studies have indicated that while students express a desire for follow-up and commitment devices, these mechanisms do not consistently translate into improved performance and, in some cases, may even result in lower completion rates. For instance, Bisin and Hyndman [20] identified a demand for commitment but found, in contrast to Ariely and Wertenbroch [18]'s findings, that self-imposed deadlines did not increase task completion rates among students. Additionally, Bisin and Hyndman [20] discovered that students exhibiting present biased preferences tended to procrastinate in single-task settings but exhibited improved self-control in repeated-task scenarios. Dobronyi, Oreopoulos [21] investigated the effects of online goal-setting treatments and reported no discernible impact on grade point average, course credits, or second-year persistence. Furthermore, Burger, Charness [22] determined that evenly spaced interim deadlines led to reduced completion rates.

3 Experimental design

The field experiment started on the first day of an introductory math course in the fall semester 2021. The course consisted of a one-week bootcamp with repetition, four weeks of lectures, one week fall break, followed by eight weeks of lectures. The students were required work with weekly exercises and submit a given problem set. The students were expected to submit and get approved 5 of 10 problem sets to sit the exam.

All students were given information about the field experiment, informed it is voluntary to participate[1]. The course teacher did not have any access to information about the participants during the experiment.

At the beginning of the study, the students filled out a questionnaire about their study habits. The survey was based on selected psychometric instruments from Svartdal [3] and Choi and Moran [4]. The questionnaire was administered digitally in class via their phones, so the students could opt-out without being noticed. Next, after a break, the students gave math test[2] as an ordinary part of the course, that all students must take. The math test measured the previous knowledge and understanding of basic concepts in mathematics related to the syllabus of the course. After the session, the second researcher distributed the participants according to their score on procrastination and put them in different bins of the distribution (section 3.2). The researcher then drew randomly from each bin and assigned the students to the treatment and control group. This partition and randomization ensured that participants in the treatment and control span the entire distribution of procrastination. The course required the students to pass 5 out of 10 mandatory work requirements. After the 6th problem set was published, an SMS nudge was sent to the treatment group. The message emphasized research-based insight that using “goal setting” to hand in 3 more homework’s (in addition to the 5 mandatory ones) can lead to improved performance in mathematics. The exact language of the text was as follows: *Hello, would you like to do well at the exam in mathematics? According to research, you can do it if you set a goal to hand in at least three problem-sets. Kind regards the research project by “name of researchers”.* The main teacher was not aware of who received the digital follow-up, and the students were told not to inform the teacher of the same. After the deadline of the seventh problem-set, we sent a reminder to the treatment group. The exact language of the text was: *Hello, there are only three more problem sets. We recommend that you set a goal to deliver all three. Then you have a good chance of succeeding in the math exam. You can do it! We cheer for you! Kind regards the research project by “name of researchers”.*

Both nudges were only sent to the treatment group and not the control group. We argue that the two interventions are slightly different, with the first informing the students that research shows promising results from setting a task-based goal, and the second offers additional mental support.

[1] All students could participate in the survey and math test without participating in the research project. We have not paid any of the participants in the study. Moreover, we obtained informed consent. The informed consent was obtained using the guidelines from the NSD. NSD also reviewed the data collection, storage, and personal information.

[2] The math test was developed based on 23. Johnson, M. and E. Kuennen, *Basic math skills and performance in an introductory statistics course.* Journal of statistics education, 2006. **14**(2). and 24. Ballard, C.L. and M.F. Johnson, *Basic math skills and performance in an introductory economics class.* The Journal of Economic Education, 2004. **35**(1): p. 3-23.

3.1 Data distribution

The class had 139 students eligible to sit the exam. 13 students did not show up to the exam. The population of students who finished the course with a grade[3] is 126. 83 participants filled out the questionnaire. 70 consented to be part of the experiment. 9 students either dropped out before the intervention, after the intervention, or did not show up to the exam. In the end, our sample consisted of 61 participants. 31 students in the treatment group and 30 in the control. We compare our sample to the overall population of the students in the class on the classification math test on the first day. Figure 1 shows the two cumulative distributions of the math score. The cumulative distributions of math scores are almost identical; hence we argue that the sample is a good representation of the population. E.g., In the sample, 84.5% of the students' answers correct on 50% or less of the classification test. In the entire class population, the same fraction is 82.1%. Similarly, 36.2% of the students' answers correct on 30% or less in the sample as compared to 37.1% in the entire population.

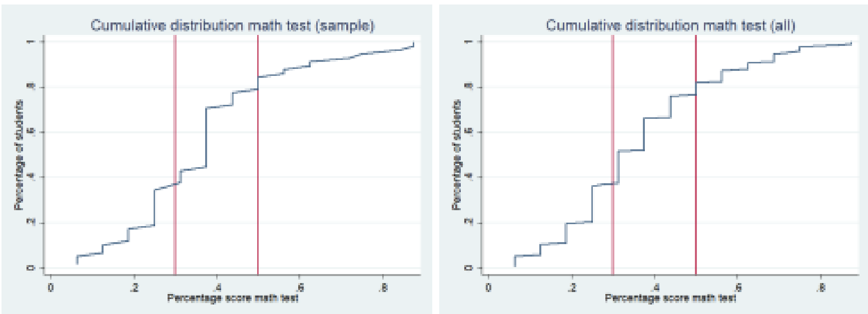

Fig. 1. This figure shows the cumulative distribution of the classification test for our sample (left) and the entire class (right).

3.2 Procrastination: Randomization of treatment and control group

The original Pure Procrastination Scale (PPS) developed by [25] and subsequently translated by Svartdal [3] measured procrastination using the 12 items. With an aim of keeping the number of questions in the survey limited, studies employing PPS in English [25], Norwegian [3], Swedish [26] and French [27] were looked at and the top six items with highest factor loadings were selected. We employ exploratory factor analysis (Table 1)[4] in line with best practices employed in prior literature [3, 25, 27] and look at the extent of common variance among the variables, KMO and Bartlett's Test of

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[3] At the end of the semester the exam was an oral exam (graded A-F) administered by 3 groups of professors, consisting of one internal and one external grader. The internal grader quizzed the student and the external grader set the final grade based on the students' performance.

[4] We employ steps prescribed by 28. Hair, J., et al., *Multivariate data analysis*. 5th ed. 1998: Prentice Hall, New Jersey.. As an extraction method, principal components analysis (PCA) was employed.

Sphericity. We employ the factor analysis using SPSS. As shown in Table 1, the results are comparable with prior literature i.e., all items load on one factor which results in 63.7% of the variance loading on the first factor with a high KMO (0.89), Bartlett's test is significant ($p < .001$) and Cronbach's $\alpha = 0.89$.

Table 1. Items, descriptive statistics, and factor loadings for PPS.

Item	Mean	SD	Loadings	Cronbach's α	Construct
PRO_1	2.85	1.06	.65		
PRO_2	3.10	1.09	.75		
PRO_3	2.87	1.20	.85	0.89	Pure Procrastination
PRO_4	3.02	1.19	.84		
PRO_5	3.00	1.16	.79		
PRO_6	2.10	1.12	.88		

Rethinking behaviours associated with procrastination, Chun Chu and Choi [29]) present the the possibility that not all forms of procrastination lead to negative consequences. They distinguished two different types of procrastination: passive and active procrastination (AP). According to them, "active procrastinators are type of procrastinators who use their strong motivation under time pressure to make intentional decision to procrastinate, to be able to complete tasks before deadlines, and achieve satisfactory results"[4, 29-31]. In this study, we employed the 16 item survey developed by Choi and Moran [4] and as with the PPS scale used 8 items (i.e. 2 items for each construct) as shown in Table 2. The items load on three factors which explains 63.2% with a KMO of 0.598 and Bartlett's test is significant ($p < .001$). In line with Choi and Moran [4])'s original study, intentional decision to delay (IDD) and ability to meet deadlines (AMD) load of two factors. The third factor is a combination of outcome satisfaction and preference for pressure, and was named satisfying outcomes under pressure (SOUP)[5] [30, 31].

Table 2. Items, descriptive statistics, and factor loadings for Active Procrastination.

Item	Construct	Mean	SD	Factor Loadings			α
PRO_7	SOUP	3.38	1.02	0.77			0.66
PRO_8		2.34	1.02	0.59			
PRO_9		3.56	0.85	0.84			
PRO_10		3.66	0.96	0.57			
PRO_11	IDD	3.39	0.92		0.82		0.66
PRO_12		2.62	1.11		0.82		

[5] "This unexpected finding, which continued to be present after confirmation that reverse-coding of items was completed accurately, conflicts with previous findings that the subscales point to a composite form of active procrastination (Chu & Choi, 2005) and are positively correlated with one another (Choi & Moran, 2009)" 31. Hensley, L.C., *Reconsidering active procrastination: Relations to motivation and achievement in college anatomy*. Learning and Individual Differences, 2014. **36**: p. 157-164..

PRO_13	AMD	3.38	1.16			0.79	0.54
PRO_14		3.59	1.06			0.82	

The students were distributed of the students along the four dimensions (one from the Pure procrastination scale and three from the active procrastination scale). Due to the relatively small sample size, the sample were spilt into two equally sized groups i.e., least and most procrastinators, to ensure treatment along the entire dimension of procrastination. Then, half of the least procrastinators and half of the most procrastinators were randomly drawn for treatment.

3.3 Outcome variables

There are two outcome variables (i) number of homework's submitted and (ii) final grade in the course. As discussed earlier, students while the students are expected to submit at least 5 work requirements to qualify for the exam, only 90% of our sample submits the first 5. However, since the first nudge is sent out with 10% students' non-submissions, we adjust for this and subtract the mandatory five, to get a measure of additional work requirements submitted i.e., "Additional WR = total – 5".

27 students (44.26%) in our sample did not submit any additional work requirements. 78.69% of our sample submitted 2 or less additional work requirements[6]. However, the sample and the population differ slightly by having more students submitting more than 4 additional work requirements. Similarly, we test the distribution of final grades. Students in Norway are graded on a scale from A – F, where F is not passed and find that there are relatively more A and D students in our sample compared to the overall population. Moreover, there appear to be fewer E and F students 13 in our sample than in the overall population of the course.

4 Results

4.1 Research question 1

This section describes our results to the first research question. Do students who identify as non-procrastinators hand in more exercises and obtain better academic scores compared to procrastinating students?

Table 3 inspect the conditional correlations between the exercises handed in and the procrastination factors. Model 1 consists of the four procrastination factors. This is our baseline model. Model 2 to 4 consists of the baseline model with covariates.

There is a negative relation between factor (i) Pure procrastination scale and the number of additional homeworks submitted. A student who self-identifies as a procrastinator submits fewer homeworks compared to a less procrastinating student. There is no relation between the other three factors and additional homeworks submitted. There

[6] We tested whether the sample distribution and population distribution are different using the Kolmogorov-Smirnov equality-of-distribution test. They are not statistically different.

is no relation between the score on the classification test and homeworks submitted, nor do male students submit more homeworks. Older students (compared to 19 - 20 years) submit more homeworks. Our baseline model (1) consisting of the procrastination factors can explain 24.1% of the variation in homeworks submitted. Model 4 which is the baseline model with covariates explain 34.1% of the variation.

Table 3. Correlations between additional work requirements and procrastination factors.

	(1)	(2)	(3)	(4)
VARIABLES	1	2	3	4
Pure Procrastination Index	-0.736***	-0.708***	-0.754***	-0.747***
	(0.234)	(0.239)	(0.257)	(0.256)
Outcome and pressure	0.121	0.269	0.210	0.0559
	(0.187)	(0.230)	(0.226)	(0.248)
Intentional decision to procrastinate	-0.255	-0.276	-0.341	-0.342
	(0.204)	(0.208)	(0.214)	(0.219)
Ability to meet deadlines	0.402*	0.348	0.360	0.364
	(0.208)	(0.215)	(0.224)	(0.219)
Classification		-0.0143	0.0105	0.0629
		(0.0630)	(0.0673)	(0.0630)
Group(gender) = 2, Male			-0.457	-0.597
			(0.376)	(0.380)
Group(age) = 5, 21-23				0.868**
				(0.379)
Group(age) = 6, Over 23				0.872*
				(0.490)
Constant	1.295***	1.429***	1.566***	0.729
	(0.174)	(0.427)	(0.468)	(0.541)
Observations	61	58	58	58
R-squared	0.241	0.270	0.286	0.341

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Tabel 4 displays the conditional correlation between the final grade, the procrastination factors and covariates. Model 1 consists of the four procrastination factors. Model 2 to 5 is the baseline model with covariates. There is no relation between the two factors (i) Pure procrastination index and (iv) Ability to meet deadlines and the final grade. There is a negative relation between factor (ii) Outcome/Pressure and the final grade, and a positive relationship between factor (iii Intentional procrastination and the final grade.

Students with a higher score on the classification test score higher on the final exam. Students who submit more additional work requirements score higher on the final grade. Older students (compared to 19 - 20 years) score higher on the final exam.

Finally, there is no relation between the gender of the student and the final grade. The full model 5 can explain 43% of the variation in final grade.

Table 4. Conditional correlations between final grade and procrastination factors.

	Final grade				
VARIABLES	(1)	(2)	(3)	(4)	(5)
Pure Procrastination Index	0.166	-0.0724	0.254	0.312	0.247
	(0.286)	(0.253)	(0.296)	(0.330)	(0.352)
Outcome and pressure	-0.116	-0.140	-0.265	-0.215	-0.451**
	(0.182)	(0.221)	(0.210)	(0.213)	(0.198)
Intentional decision to procrastinate	0.364*	0.295	0.423*	0.490**	0.445**
	(0.209)	(0.249)	(0.230)	(0.241)	(0.219)
Ability to meet deadlines	-0.0285	0.128	-0.0328	-0.0509	-0.00720
	(0.261)	(0.244)	(0.246)	(0.261)	(0.255)
Classification math score		0.208**	0.214***	0.192**	0.287***
		(0.0909)	(0.0800)	(0.0910)	(0.0895)
Additional work requirements			0.461***	0.483***	0.356**
			(0.145)	(0.142)	(0.139)
Male				0.427	0.157
				(0.489)	(0.480)
Age: 21-23					1.384***
					(0.479)
Age: Over 23					1.602***
					(0.531)
Constant	4.754***	3.509***	2.850***	2.692***	1.429**
	(0.216)	(0.581)	(0.523)	(0.485)	(0.605)
Observations	61	58	58	58	58
R-squared	0.072	0.185	0.308	0.319	0.430

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.2 Research question 2

The two main outcome variables of interest are the work requirements (HW) and the final grade on the exam (G). First, we analyze the impact of the nudge on the number homeworks submitted. We measure this in two different ways: (i) the number of homeworks and (ii) whether the number of homeworks is strictly above the mandatory requirement. The results are displayed in Table 5. There is no relationship between the the nudge and the homeworks submitted.

Next, we use the estimates from the previous analysis to inspect the causal effect of homeworks on final grades. First, homeworks submitted is a choice and therefore not exogenous. However, we can use the nudge as a treatment to capture the exogenous part of submitting homeworks, while keeping the choice part out. We then use the estimated relationship between the nudge and the homeworks as an instrument variable to estimate the causal effect of homeworks on final grade.

The results are displayed in Table 6. Model 1 estimates the raw correlation between homeworks and final grade. These estimates are not causal because submitting more homeworks is a choice. Model 2 has used the estimates from Table 5 to estimate the effect of the nudge on the homeworks as a first-stage, and then used these estimate to estimate the causal effect of homeworks on grades. There is no relation between additional homeworks submitted and the final grade.

Model 3 estimates the raw correlation between submitting more than the mandatory and the final grade. These estimates are not causal for the same reason as before. Model 4 then uses the results from Table 5 to estimate the first-stage effect of the nudge on submitting more than the mandatory, and the uses these estimates to estimate the causal effect of homeworks on grades. Also here, we find no causal effect between submitting more than the mandatory level and the final grade.

For both these results, the first-stage instrument is weak, with an F-statistic of 0.5 or 0.2 as displayed in Table 6. This means that our low-cost intervention was not strong enough to nudge the students.

Table 5. First-stage OLS regression of homework and treatment.

VARIABLES	(1) Number of HW (OLS)	(2) Uptake (OLS)
treat = 1, treated	-0.272	0.0612
	(0.387)	(0.138)
Pure Procrastination Index	-0.743***	-0.213***
	(0.260)	(0.0777)
Outcome and pressure	0.0705	-0.0482
	(0.249)	(0.0734)
Intentional decision to procrastinate	-0.385	-0.0670
	(0.236)	(0.0759)
Ability to meet deadlines	0.386*	0.115
	(0.217)	(0.0775)
group(alder) = 5, 21-23	0.881**	0.427***
	(0.391)	(0.141)
group(alder) = 6, Over 23	0.888*	0.409**
	(0.497)	(0.186)
group(kjnn) = 2, Male	-0.638	-0.152
	(0.386)	(0.141)
kartlegging	0.0776	0.0303
	(0.0690)	(0.0266)
Constant	0.795	0.157
	(0.549)	(0.201)
Observations	58	58
R-squared	0.347	0.291

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6. OLS and 2SLS regression of final grades and homework.

	Final grade		Final grade	
	(1)	(2)	(3)	(4)
VARIABLES	OLS	2SLS	OLS	2SLS
Work requirements	0.356**	-1.109		
	(0.139)	(1.470)		
Work requirements (> the mandatory level)			0.702	4.938
			(0.454)	(6.549)
Pure Procrastination Index	0.247	-0.848	0.130	1.027
	(0.352)	(1.170)	(0.346)	(1.380)
Outcome and pressure	-0.451**	-0.370	-0.400*	-0.210
	(0.198)	(0.237)	(0.219)	(0.362)
Intentional decision to procrastinate	0.445**	-0.0572	0.376	0.701
	(0.219)	(0.562)	(0.233)	(0.550)
Ability to meet deadlines	-0.00720	0.526	0.0379	-0.472
	(0.255)	(0.654)	(0.259)	(0.738)
Group(age) = 5, 21-23	1.384***	2.655*	1.392***	-0.429
	(0.479)	(1.339)	(0.484)	(2.889)
Group(age) = 6, Over 23	1.602***	2.879**	1.623***	-0.124
	(0.531)	(1.358)	(0.549)	(2.782)
Group(gender) = 2, Male	0.157	-0.718	0.0577	0.741
	(0.480)	(1.010)	(0.489)	(1.138)
Classification	0.287***	0.379***	0.286***	0.143
	(0.0895)	(0.121)	(0.0941)	(0.246)
Constant	1.429**	2.496*	1.567**	0.838
	(0.605)	(1.333)	(0.644)	(1.189)
Observations	58	58	58	58
R-squared	0.430	0.370	0.393	0.370
First-stage instrument				
Treated		-0.272		0.0612
Robust standard error		(0.287)		(0.138)
F statistic for IV in first stage		0.5		0.2

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Conclusion

We have looked at how study habits are related to homeworks and final grade. We find that students who self-identify as procrastinators submit fewer homeworks. We do find significant correlation between the study types and the final grade, but only for two of the four dimensions we use to measure procrastination. We find no effect of the nudge on the students behavior, and as a result we find no causal effect of homeworks on final grades. Our results are contrary to Clark et al. [2]. They find that students who are nudge hand in more homeworks and this affects their final grade. Our results are in line with papers showing that students are not easily nudged (e.g. [2] and [21]). Our main contribution is that we can control for the study habits of the students. Previous studies on nudging in traditional, blended, and online educational settings have highlighted the advantages of digital interventions, such as emails, LMS nudges and SMS. However, our research found no significant impact of the nudge on student behavior. This discrepancy may result from the timing or intensity of the nudge in our experiment. Further research could introduce an SMS nudge in courses where assignments or homework are optional. Additionally, the intensity of the nudge should be increased and distributed over a longer time period.

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