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Procrastination and grades: Can students be nudged towards better outcomes?

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ABSTRACT

This study starts by examining the relationship between procrastination and grades. I use a large sample (n = 17,241) of timed submissions of online assessments, where having multiple observations for each individual makes it possible to control for individual fixed effects. The data confirm a significant negative relationship between procrastination and grades. To address procrastination, two “nudges” encouraging earlier submission were tested with a smaller class group. The first was a communication about social norms relating to submission times; and the second was an information nudge highlighting grade disadvantages of late submission. Disappointingly, neither nudge led to earlier average submission times. This finding adds to a small body of work suggesting that nudges might be less effective when trying to change habitual behaviours.

1. Introduction

Procrastination of less pleasant activities is a common human behaviour, not least among college students. Students might get behind in readings or assignments; or procrastinate exam preparations. This problem has been acknowledged for some time: Solomon and Rothblum (1984) noted that at least 46% of college students consider themselves serious procrastinators; while Steel (2007) noted that 80–95% of college students regularly procrastinate when working on academic tasks, and 95% of college students would like to reduce procrastination.

Procrastination has been widely found to have a negative impact on grades (e.g. Michinov et al., 2011 and references therein). The negative consequences of performing below potential can, of course, even extend to failing a course. Welfare losses associated with below expected performance or having to repeat a course make procrastination an ideal candidate for “nudges”. According to Sunstein (2014b), nudges (small changes aimed at impacting behaviour without removing freedom of choice) are appropriate where behaviour changes would improve welfare over time.

This research considers two main goals. The first is to see whether the previously found negative relationship between procrastination and grades can be replicated in a large sample. To answer this question, grades and submission times are used from over 17,000 online assessments across 4 undergraduate economics modules in the first semester of 2020. Having multiple assessments for each student allows for fixed effects panel regressions to be used, controlling for individual level differences in procrastination and performance.

The link between submission times and grades is likely due at least in part to differences in motivation and engagement with the course (where those who are more motivated and engaged might be more likely both to perform better and to submit earlier). I use a smaller group with additional data to investigate measurable aspects of course engagement to see whether these moderate the

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procrastination/grade relationship.

The second goal, is to establish whether two nudges (a social norms communication; and information about the impact of procrastination on grades) can reduce procrastination on assignments in an undergraduate course. Assignment submission times are used to see whether procrastination behaviour changes with either of the nudges. Finally, since the first nudge focuses on correcting beliefs about normative submission behaviour, beliefs about others' submission times are elicited to see whether these predict students' procrastination.

The study therefore considers the following research questions: 1. Do these data support the finding that procrastination (measured as later submission times) has a negative association with grades? 2. Does the strength of this relationship vary with effort, measured by engagement with lectures and study materials? 3. Does either of the tested nudges reduce procrastination, measured as the time remaining until assignment deadline? 4. Do beliefs about others' procrastination predict students' own procrastination behaviour?

Using the large sample of over 17,000 online assessments, I find clear support for a negative relationship between later submission times and grades. For the remaining research questions, I consider a smaller group of second year microeconomics students for whom detailed data on course engagement is available. With this smaller group, the negative procrastination-grade relationship persists when student effort (engagement with course materials) is included as a control.

The nudge communications were tested first in a within-subject experiment in a smaller group of 145 second year students in the 2020 academic year. In order to also include a more robust, between-subject version of this experiment, the slightly larger 2021 class group for the same second year course was randomly divided into 2 groups, where one group was treated with the more promising of the two nudge communications.

No reduction in aggregate procrastination behaviour was found with either of the nudge communications, in either group of students. The lack of reduction in procrastination in the social norms nudge is unsurprising *ex post*, since the data also showed that students' beliefs about procrastination behaviour of others did not predict their own procrastination. While disappointing, the finding of no aggregate behaviour change following the nudges ties in with a handful of studies suggesting that nudges might be less effective at changing habitual behaviours.

2. Literature

Procrastination is frequently modeled as an outcome of time inconsistent preferences: in the academic context, students' "future selves" often regret the procrastination decisions of their "earlier selves" (Solomon and Rothblum, 1984; Steel, 2007). Overcoming self-control challenges can have significant impacts on academic performance: grades depend not only on intellectual aptitude, but also on time management and on the self-discipline needed to exert effort and concentration over extended time periods (Koch et al., 2015; Michinov et al., 2011). Duckworth and Seligman (2005) found that self-discipline is a better predictor of academic performance than IQ.

A number of studies have found a negative relationship between procrastination and academic success (e.g. Ariely and Wertenbroch, 2002; Arnott and Dacko, 2014; Jackson et al., 2003Wong, 2008; Romano et al., 2005). De Paola and Scoppa (2015) used college enrolment timing (day 1–7 in a one week window for enrollment) as a behavioural measure of procrastination, and found that students who procrastinated had lower final grades at high school, lower placement test scores and acquired fewer credits in their academic careers. Beattie et al. (2018) found higher self-reported academic procrastination among students whose first year college average was well below their high school average grade. However, the negative relationship between procrastination and grades is not universally found: a few papers note the absence of a significant link between procrastination and grades (e.g. Howell et al., 2006; Schraw et al., 2007).

A few studies have also considered how effort interacts with procrastination or patience. Non and Tempelaar (2016) found no difference in effort (time spent on a course) between more and less patient students. However, they did record lower grades for less patient individuals. Similarly, Wong (2008) found that time-inconsistent behaviour was associated with worse performance, even after controlling for actual time spent on the course.

2.1. Reducing procrastination

One way in which procrastination has been addressed in the literature is through the use of binding deadlines as commitment devices. Theoretical work by O'Donoghue and Rabin (2008) suggests that imposing a schedule on employees (or, in our context, students) would lead to better outcomes than leaving the timing of project work to employees' own discretion. In the academic procrastination literature, results with binding deadlines have been somewhat mixed. Ariely and Wertenbroch (2002) found that students performed better when forced to manage their procrastination behaviour, and Himmler et al. (2019) noted that soft commitment devices (non-binding commitments to write exams on a recommended schedule) increased both likelihood to participate in exams and exam pass rate. However, Burger et al. (2011) found lower completion rates when adding interim deadlines for completing a required number of study hours; and Bisin and Hyndman (2020) did not find increased or earlier completion among those students who either chose or were given a deadline.

2.2. Nudges

Since the publication of Thaler and Sunstein's best-selling book of the same title (Thaler and Sunstein, 2008), "nudges" have become increasingly widely used tools in both academic research and public sector policy making. Nudges take the form of small, usually inexpensive changes that encourage people to adopt desired behaviours, without limiting their freedom of choice.

Considering procrastination, default nudges (automatic enrolment in savings plans with the option to opt out, rather than having to choose to opt in) have been used with success to significantly increase savings among those who might otherwise have put off savings decisions (e.g. Madrian and Shea, 2001; Thaler and Benartzi, 2004).

In a short paper on nudges, Sunstein (2014a) details 10 recommended nudge approaches, including social norms communications, reminders, increases in ease/convenience and informing people of the consequences of their own prior choices. Two of these are used in this experiment: social norms communications and information on consequences of prior choices.

2.2.1. Social norms communications

Social norms communications have been used successfully in a variety of contexts. These include reducing the number of antibiotics prescribed by General Practitioners (Hallsworth et al., 2016); decreasing alcohol use in colleges (Wechsler et al., 2003); reducing sexual violence against women (Fabiano et al., 2003); increasing purchasing of healthy food (Aldrovandi et al., 2015); increasing the participation of women in the work force (Bursztyn et al., 2018); increasing participation in a Teach for America program by high achieving college graduates (Coffman et al., 2017); and reducing energy use (Ayres et al., 2013). These were also successful when sent as reminders to reduce student procrastination on computer science projects (Martin et al., 2015).

Prentice and Miller (1993) noted that people choose their own behaviours based at least in part on their beliefs (including beliefs about others' decisions), which are not always accurate. Social norms communications address these errors in decision making by providing information on others' behaviour or beliefs. Theorists propose a few explanations for the impact of social norms communications on behaviour. Banerjee (1992) attributes this to people's beliefs that peer's decisions are made based on private information that is relevant to payoffs (see also, Ellison and Fudenberg, 1993). Festinger (1954) suggested that adherence to social norms might reflect a preference for conformity to these norms; while Akerlof (1980) proposed a belief that not conforming would lead to a loss of utility and social status.

2.2.2. Information nudges

Damgaard and Nielsen (2018) discusses information nudges used in education, primarily aiming at letting parents know more about their children's performance. As these authors note, university students might not have all the information they need to judge how their current performance and behaviour might influence their likelihood of graduating. Most of the studies included in the Damgaard and Nielsen (2018) analysis use information about rank or relative performance as nudges, with mixed success. For example, high performing students sometimes reduced effort in response to ranking nudges. Martin et al. (2015) found a significant reduction in procrastination when computer science students were sent email alerts noting their progress relative to others in the class. Martinez (2014a) experimented with information nudges in a MOOC online context, and found that informing students of their rank in the class led to increased effort, and in some cases also to improved grade outcomes. In another MOOC-based information nudge study, Martinez (2014b) found a positive effect (17% increase) on course completion from telling a treatment group of students that performance was worse for students who chose to do the quizzes later than for those who did them earlier. However, Martinez notes that the baseline for course completion was very low, and that the effect varied by country, with students from some countries showing reduced completion when exposed to the information nudge.

3. Methodology

3.1. Procrastination data

To answer the first research question, data were gathered from the Blackboard Learning Management System for all online assessment tasks for 4 undergraduate economics courses at the University of Pretoria in South Africa in the first semester of 2020. Almost all of the assessment tasks for the first semester (mid-February to late June) in 2020 took place online. Smaller assignments were conducted online throughout most courses, and the COVID-19 lockdown in South Africa starting in late March resulted in midterm (semester) tests and exams having to be written as online assessments too.

The Blackboard system automatically tracks submission times for all assignments, as well as recording all grades. This gave a sample of over 17,000 assignments, allowing for a very robust measure of the relationship between procrastination and grades.

To answer the remaining research questions, data were gathered from a smaller sample of 145 students registered for a second year microeconomics course taught by the author, for which detailed data on course engagement was available. The within-subjects nudge experiment was also conducted in this class in 2020, while the between-subjects nudge experiment was conducted in a separate class group of students taking the same second year microeconomics course in 2021.

3.2. Experiment

To investigate the impact of two nudges aimed at reducing procrastination, students in the second year microeconomics class received nudge communications during the course. These students were also invited to participate in an experiment task, where they

What percentage of the EKN 244 class will submit problem sets more than 12 hours before the due time?

Percent submitting early	Probability that this percentage will submit early	Payout if this is the true percentage
0-10%	0	R0
11-20%	0	R0
21-30%	0	R0
31-40%	0	R0
41-50%	0	R0
51-60%	0	R0
61-70%	0	R0
71-80%	0	R0
81-90%	0	R0
91-100%	0	R0

Total tokens allocated (you should allocate 100 tokens)

0 KEEP ALLOCATING TOKENS UNTIL YOU HAVE USED ALL 100 TOKENS

(a)

What percentage of the EKN 244 class will submit problem sets more than 12 hours before the due time?

Percent submitting early	Probability that this percentage will submit early	Payout if this is the true percentage
0-10%	0	R35
11-20%	0	R35
21-30%	0	R35
31-40%	0	R35
41-50%	0	R35
51-60%	10	R45
61-70%	30	R65
71-80%	40	R75
81-90%	20	R55
91-100%	0	R35

Total tokens allocated (you should allocate 100 tokens)

100 DONE

(b)

Figure 1. Belief elicitation task interface (a) Blank interface; (b) Example complete interface.

were asked to answer a few survey questions about their own procrastination and beliefs about the impact of procrastination on grades. In addition, students were asked to report their beliefs about the distribution of submission times for tutorials in the course. Reporting of true subjective beliefs was incentivised with monetary payments based on the accuracy of the reported beliefs. Of the 145 students registered for the course, 74 completed the beliefs task.[1]

3.2.1. *Beliefs*

To ascertain whether students who procrastinated did so in part based on erroneous beliefs about the behaviour of other students, I elicited beliefs about the proportion of students who submitted tutorial assignments at least 12 h before the assignment deadline. Students completed 9 graded tutorials over the duration of the course. Tutorials were made available on Tuesday afternoons, and had to be submitted by midnight on Sunday.

Students were asked to report their beliefs about the proportion of students in the class who would submit tutorial assignments at least 12 h before the deadline. An Excel-based tool was used to elicit students' beliefs in the form of a probability distribution. Manski (2004) argues that probability distributions allow for a better understanding of the uncertainty surrounding point estimates of beliefs. Beliefs were elicited as subjective probability distributions in an incentive compatible way with a widely used approach (Eil and Rao, 2011, Di Girolamo et al., 2015 and Harrison et al., 2017): Participants assign tokens to different intervals in a distribution of possible outcomes. The number of tokens placed in each interval indicates the respondent's believed likelihood that the outcome will fall in that interval. The incentive compatible (Selten, 1998) quadratic scoring rule (Matheson and Winkler, 1976) was used to calculate the monetary payments received by respondents when the true answer lies in a given interval. Respondents could experiment with different token allocations in the excel tool to see how the payment they would receive would vary based on the tokens they allocated to different intervals.[2] The blank and example completed interface are shown in Figure 1, and the full instructions associated with this task are included in the appendix.

Students had already had a lecture talking about some concepts in behavioural economics, part of which was a discussion of the benefits of incentives for accurate belief elicitation. This, together with the experiment instructions, was expected to encourage students to report their beliefs truthfully.

3.2.2. *Within-subject nudge experiment*

In both the 2020 and 2021 courses, students completed nine tutorial assignments during the semester course. With the exception of the second assignment, all were multiple choice questions and automatically graded on the Blackboard Learning Management System, avoiding any risk of grader bias. Procrastination for these assignments was measured as the time between each student's submission

[1] Students who chose to complete the beliefs task had slightly higher grades and later submission times, on average. These students were also more likely to be female than those who did complete the task. Details are included in the Appendix.

[2] With the quadratic scoring rule, participants would receive the maximum payment (ZAR 100) if they placed all 100 tokens in the correct interval (this would happen if, for example, a respondent had correctly assumed that between 31% and 40% of students would submit timeously, and had put all of their tokens in this interval). Participants who were less certain about the true percentage might choose to distribute tokens across more possible intervals in the distribution (as in Figure 1b). While this would not allow the full ZAR 100 payment, it would mean that the participant would receive some payment whatever the true percentage turned out to be. The more tokens allocated to an interval, the more the payment would be if that interval turned out to contain the true percentage.

Table 1
Summary data.

	All classes		Single class 2020		Single class 2021	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Age	19.91	1.80	21.16	1.71	21.11	1.46
Gender: Male	0.49		0.46		0.53	
Gender: Female	0.51		0.54		0.46	
Race: Black	0.51		0.68		0.58	
Race: Indian	0.07		0.05		0.06	
Race: White	0.42		0.25		0.34	
Year: First	0.67		0.0		0.0	
Year: Second	0.13		1.0		1.0	
Year: Third	0.20		0.0		0.0	
Grade	68.71	18.09	63.75	25.93	69.28	26.37
Time to deadline (seconds)	70,995	143,995	111,010	139,896	114,388	139,415

N = 17241 assessments, N = 1006 assessments, N = 1531 assessments

time and the assignment deadline time.[3] Since all assignments were submitted online through the Blackboard System, the exact submission time was automatically recorded for all assignments.

Because of the small class size, a within-subject design was used in 2020 to investigate the impact of the two nudges. Students first completed three tutorial assignments to give a baseline read of the extent of their procrastination. The first nudge communication was sent after tutorial 3; and the second after tutorial 6. Submission times were then compared for these groups of tutorials.

Nudge 1 (social norm): The first nudge was intended to demonstrate to students that procrastination is less common than they might have assumed. It was expected that students would underestimate the number of people who submitted ahead of time when responding to the belief elicitation task. In this case, a social norms nudge communication correcting this misperception might have been effective at reducing procrastination.

The promised incentive payment for the belief elicitation task was based on the submission times observed in the first three tutorial assignments. I had planned simply to report the true percentage of students submitting prior to the final 12 h for these 3 tutorial assignments as the social norms nudge (for previous courses, this was 85%). However, contrary to first semester economics undergraduate courses, only 39% of students in this second semester undergraduate course submitted the tutorial assignments 12 h or more before the deadline.

Since an early submission proportion of 39% did not provide a compelling nudge to submit earlier, I modified the original planned nudge to a more persuasive social norms communication. Specifically, the nudge communication reported the proportion of students who had submitted similar assignments at least 12 h before the deadline across undergraduate economics courses. This was announced in class, included in the lecture slides, and put in an announcement email sent via the Blackboard Learning Management System. The announcement read: "Try not to leave your tutorials to the last minute: Looking at first semester economics courses, 85% of students submit assignments more than 12 h before the deadline (this figure is based on assignments like ours with a few days to complete). Also, based on responses to the experiment survey questions, 93% of you would prefer to submit more than a few hours before the deadline."

However, because of the incentivised belief elicitation task, the percentage of students submitting early in the specific undergraduate course had to be reported to students as well. This far lower proportion (39%) of timeous submissions was unfortunately likely more salient to students than the proportion included in the nudge communication (85%). Attempting social norms nudges where the social norm is one of non-compliance is widely recognised as ineffective at best, and counterproductive at worst.

The impact of the social norms nudge was assessed by considering online submission times of the fourth, fifth and sixth tutorial assignments; and comparing these to submission times for the pre-nudge tutorial assignments.

Nudge 2 (information): The second nudge communicated information about performance differences between students who submitted early (more than 12 h before deadline) and students who submitted late.[4] The average tutorial grade for relatively late submissions (within 12 h of the deadline) was compared to the average grade for relatively early submissions (more than 12 h before the deadline), giving a ratio of 1.21. The nudge communicated to students, both in class and by email sent via the Blackboard communication tool, was: "Last minute submissions can cost you a lot of marks: on average, students who submitted their 244 tutorials more than 12 h ahead of the deadline received grades that were 21% higher than those who submitted later (in the last 12 h before the deadline)."

The impact of this second nudge was assessed by considering online submission times for the seventh, eighth and ninth tutorial assignments, and comparing these to online submission times for earlier tutorial assignments.

[3] Late submissions (after the deadline submission time) were not accepted: students could not start an assessment in the system after its due date had passed. Any attempt to start or submit an assignment after the due date resulted in a missing (zero) grade for the assessments considered in this research. I therefore consider submission times close to the deadline, rather than post-deadline submission times, as indicative of procrastination.

[4] This information was based on the first five tutorials, in order to have the nudge ready to report after the sixth tutorial was submitted, but before the seventh tutorial was made available.

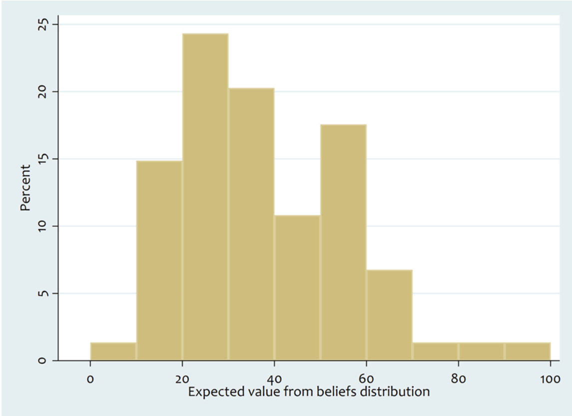

Figure 2. Histogram showing expected value of elicited belief distributions (n = 74).

3.2.3. Between-subjects nudge experiment

Since the main study used a within-subject design, making it difficult to disentangle changes over time from changes based on the nudges, the information nudge was also tested in a between-subjects design with a slightly bigger group of students taking the same second year microeconomics course in 2021 (n = 192). The 2021 class was randomly divided into two groups using Blackboard's group creation function (where students can be randomly divided into a given number of groups). One of the two groups received the information nudge as an email communication sent from the Blackboard system before the fourth tutorial assignment. The other group received no extra communication.

This 2021 addition was not part of the original study plan, but was added as a test for the robustness of the findings.

3.3. Data

3.3.1. Grades and submission times

The data for the main study are summarised in Table 1. For the first research question, all economics undergraduate classes (17,241 assessments) were included for the large sample analysis of the relationship between submission times and grades. For the remaining analysis, either the 2020 or 2021 single class of second year microeconomics students was included, as indicated.

3.3.2. Beliefs about submission times

The experiment data from the beliefs task are reported in Figure 2.

Recall that for the first 3 tutorials, 39% of assignments were submitted more than 12 h before the deadline. Figure 2 shows the distribution of the mean expected values from students' reported beliefs. On average, beliefs were fairly accurate, with a mean expected value from the reported probability distributions of 37.49% (s.d. 18.39). This finding was somewhat surprising given that students in this course had submitted assignments earlier in their first semester economics courses: across undergraduate economics courses with online tutorial submissions, 85% of students submitted assignments more than 12 h before the due time.

3.4. Estimation approach

For the first 2 research questions, the following simple model is estimated, where the effort variables are included for the second research question:

Research question 1:

$$Grade_{ij} = \alpha_0 + \beta_1 Submissiontime_{ij} + \gamma_i + \varepsilon_{ij} \tag{1}$$

Research question 2:

$$Grade_{ij} = \alpha_0 + \beta_1 Submissiontime_{ij} + \beta_2 Effort_{ij} + \gamma_i + \varepsilon_{ij} \tag{2}$$

$Grade_{ij}$ refers to the grade received by student i on assessment j; $Submissiontime_{ij}$ indicates the log of the time difference (in seconds) between the actual time at which student i submitted assessment j and the deadline for submission of assessment j. $Effort_{ij}$ is included for research question 2, and represents a matrix of 3 measures of the engagement of student i with the materials made available for assessment j (joining the live online lectures, watching the recorded lectures, downloading lecture slides). γ_i represents individual fixed effects for student i.

Table 2
FE regressions: association between time remaining and grade.

	Fixed Effects
ln(seconds until deadline)	0.415 * **
	(0.10)
constant	64.662 * **
	(1.014)
Observations	17241
F	16.29 * **

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

Table 3
Time remaining, effort and grades.

	OLS (1)	OLS (2)	FE (3)
Time remaining	2.261 * **	1.664 * **	1.085
	(0.594)	(0.622)	(0.658)
Age		− 1.536 * *	
		(0.639)	
Non-white		− 2.490	
		(2.819)	
Male		2.958	
		(2.487)	
Joined live lecture		1.346	− 0.714
		(1.267)	(1.35)
Watched recording		2.303 * *	− 0.512
		(1.074)	(1.031)
Accessed slides		0.999	2.177
		(2.478)	(2.416)
Constant	39.448 * **	74.502 * **	51.085 * **
	(6.475)	(14.914)	6.900)
Adj. R2/F	0.020	0.036	0.97
Obs	1006	998	1006

Standard errors in parentheses * p < 0.10, * * p < 0.05, * ** p < 0.01

Research question 3:

To answer the third research question for the within-subjects nudge experiment, submission time is regressed on a Post-nudge 1 dummy variable taking the value of 1 for tutorials completed after the social norms nudge and 0 otherwise; and a Post-nudge 2 dummy variable taking the value of 1 for all tutorials completed after the information nudge and 0 otherwise.

The simple model is as follows:

$$Submissiontime_{it} = \alpha_0 + \beta_1 PostNudge1 + \beta_2 PostNudge2 + \beta_3 Effort_{it} + \gamma_i + \varepsilon_{it} \quad (3)$$

$Submissiontime_{it}$ indicates the log of the time difference (in seconds) between the actual time at which student *i* submitted assessment *t* and the deadline for submission of these assessments. *PostNudge*1 and *PostNudge*2 indicate whether each nudge communication had been received at the time of the submission; and $Effort_{it}$ is again a vector of the measures of the engagement of student *i* with the tutorial assignments in round *t*. If the nudges were successful in reducing procrastination, the β_1 and β_2 coefficients would be positive, indicating an increase in the average time between submission and the assignment deadline following each of these nudges.

Research question 4:

To investigate the final research question, submission times are regressed on beliefs about others' submission times, beliefs about the impact of late submission on grades, and self-reported procrastination. The following simple model is estimated:

$$Submissiontime_{ij} = \alpha_0 + \beta_1 BeliefsOthers_i + \beta_2 BeliefsGrade_i + \beta_3 Procrastinate_i + \varepsilon_{ij} \quad (4)$$

The $Submissiontime_{ij}$ variable is defined as in equation 1; $BeliefsOthers_i$ is the expected value of the probability distribution reported by student *i* for the proportion of people in the class expected to submit assignments at least 12 h before the deadline; $BeliefsGrade_i$ is a dummy variable taking the value of 1 if the respondent reports believing that early submitters do slightly or much better, and 0 otherwise. The individual's degree of self-reported procrastination (reported as a categorical variable ranging from "hardly ever", coded as 0 to "often", coded as 3) is also included as $Procrastinate_i$.

Table 4
Mean Time Remaining pre- and post-nudges.

	Mean	Std. Dev.
Baseline	10.79	1.56
Post-Nudge 1	10.46	1.71
Post-Nudge 2	10.41	1.58
Ranksum z: Baseline vs. Nudge 1	2.16 * *	
Ranksum z: Nudge 1 vs. Nudge 2	0.85	

Table 5
Nudge impacts on time remaining.

	Fixed Effects
Post-Nudge 1	− 0.202 * *
	(0.102)
Post-Nudge 2	− 0.008
	(0.087)
Watched recording	0.120 * *
	(0.054)
Joined live lecture	0.314 * **
	(0.076)
Accessed slides	0.286 * *
	(0.125)
Constant	10.154 * **
	(0.153)
F	5.66 * **
Obs	1006

Standard errors in parentheses $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$

4. Results

4.1. *Procrastination and grades: Research Question 1*

Table 2 shows the result of a panel regression with student fixed effects. This approach is used to control for unobserved individual differences. For example, it might be argued that the type of student who procrastinates is also the type of student who does worse in test settings. Using individual fixed effects helps to rule out this explanation for the finding of a strong association between submission time and grades. The results show a significant association between earlier submissions and higher grades.

To test for the robustness of these findings, OLS regressions, including probit regressions looking at the likelihood of passing (receiving a grade of 50% or higher) and at the likelihood of passing with distinction (receiving a grade of 75% or higher) were estimated. Both likelihood of passing and likelihood of passing with distinction increase significantly with earlier submission times. These results are shown in the Appendix (Tables 8 and 9).

4.2. *The role of effort: research question 2*

To answer the second research question, the single class sample with data on effort (engagement with available course materials) is used. This sample includes approximately 1000 observations from weekly tutorial assignments in the 2020 second year microeconomics class, for which 145 students were registered. Table 3 reports these results.

The regressions include 3 effort behaviours related to the course material covered in each assessment: joining the live lecture, watching the lecture recording and accessing slides. Specifically, I consider whether the student joined 0, 1 or 2 of the live online lectures related to each tutorial; whether the student watched the recording from 0, 1 or 2 of the online lectures; and whether the student accessed the PowerPoint slides that were uploaded to the learning management system. Since all lectures were recorded, attendance of the live online lectures was fairly low. However, a number of students chose to watch the lecture recordings.

Column (1) considers only the time remaining variable. In column (2) demographic controls are added to the OLS regression, as well as the effort measures. Column (3) presents the fixed effects panel regression, including the effort measures. The fixed effects panel regression in column (3) shows a smaller magnitude for the relationship between submission time and grade, although the direction remains the same. When accounting for individual fixed effects, the relationship is, however, only marginally significant ($p = 0.1$). This points to the role of unobservable individual characteristics, such as ability, in explaining grades.

Interestingly, the significance of the effort variables differs between the OLS and FE regressions. In the OLS regressions, watching recordings of lectures has a significant positive relationship with grades. This falls away in the FE regression, suggesting that the link between watching lectures and grades does not persist when controlling for individual fixed effects.

Table 6
Mean time remaining for nudged and control.

	Mean	Std. Dev.
Baseline (pre-nudge) Nudge group	10.85	1.58
Control group	11.02	1.43
Ranksum z: nudge group vs. control	0.71	
Post-nudge Nudge group	10.53	1.68
Control group	10.47	1.64
Ranksum z: nudge group vs. control	0.66	

Table 7
OLS: Time Remaining and Beliefs.

	(1)	(2)	(3)	(4)
Beliefs Others	0.010	0.007	0.008	0.007
	(0.006)	(0.007)	(0.007)	(0.007)
Age		− 0.124	− 0.135	− 0.151 *
		(0.084)	(0.083)	(0.079)
Non-white		0.141	0.154	0.269
		(0.277)	(0.275)	(0.261)
Male		0.183	0.178	0.319
		(0.321)	(0.319)	(0.310)
Beliefs Grades			0.215	0.182
			(0.259)	(0.250)
Procrastinator				− 0.390 * **
				(0.125)
Constant	10.499 * **	13.031 * **	13.093 * **	13.867 * **
	(0.269)	(1.789)	(1.770)	(1.712)
Adj. R2	0.011	0.021	0.023	0.070
Obs	567	567	567	567

Standard errors in parentheses * $p < .10$, * * $p < .05$, * ** $p < .01$

4.3. Nudge impact: research question 3

4.3.1. Within-subjects experiment

For the within-subjects experiment, considering the impact of the two nudges, Table 4 shows the average time remaining (again measured as the log of the seconds remaining) until the deadline for the tutorials prior to either of the nudges (Baseline); the three tutorials immediately after the first (social norms) nudge (Post Nudge 1); and the three tutorials after the second (information) nudge (Post Nudge 2).

Successful nudging would have resulted in increases in the time remaining in the post-nudge means. Instead, a fairly small but significant decrease is seen in time remaining following the first nudge; with no significant change following the second nudge.

Recall that the first nudge was designed to point out social norms in submission times, following the beliefs task in which students' incentivised beliefs about the prevalence of early submission in the class were elicited. This incentivised task required me to report to students the true proportion of students submitting more than 12 h before the deadline. This proportion was surprisingly low for this course, at 39%. Although a more persuasive nudge communication was used (highlighting the prevalence of early submission across undergraduate economics modules), the low proportion for the specific course was likely more salient to students, since their incentive payments were based on their accuracy in predicting this proportion. It is perhaps not surprising, then, that this nudge was not successful. Perhaps the increase in procrastination (reduced time remaining before deadline) could be related to students' learning that early submission is in fact fairly uncommon.

As a robustness check for these mean comparisons, the regression results shown in Table 5 confirm the findings in Table 4: on average students procrastinated more, rather than less, following the first nudge (social norms), and did not significantly change their procrastination behaviour following the second nudge (information). Effort behaviours (joining live lectures, watching recordings of the lectures and accessing lecture slides) were associated with earlier submission times.

4.3.2. Between-subjects experiment

Since the within-subjects design of the main nudge experiment does not allow changes over time to be separated from changes due to the nudges, recall that the information nudge was tested in a between-subjects context in the 2021 class group for the same second year microeconomics course. The class of 192 students was divided into 2 randomly assigned groups, each with 96 students. This additional experiment was not part of the original study design, but was added as a robustness check for the findings with the information nudge.

The results are reported in Table 6. I first tested for similarity in submission behaviour prior to the implementation of the nudge message. The 2 groups did not differ significantly in their average pre-nudge submission times, suggesting that the randomisation was successful. The post-nudge submission times support the finding in the main experiment of no significant difference in average submission behaviour following the nudge treatment.[5]

Interestingly, although average submission time did not change, there was a slight difference in the proportion of students submitting assignments after the nudge: in the nudged group, 90% of assignments were submitted, while 86% were submitted in the control group. A Wilcoxon rank-sum test indicates that this difference is significant ($z = 2.02$, $p = 0.04$).[6] The groups did not differ in the proportion of assignments submitted prior to the nudge, with 89% of assignments submitted in both groups.

Looking at submission times for each tutorial, I did see some difference in submission times on the tutorial immediately following the nudge (tutorial 4). For this tutorial, the group receiving the nudge submitted nearly 5 h earlier on average than the un-nudged group: the mean log of seconds remaining to deadline for the nudged group was 10.78, (s.d. 1.64), while for the un-nudged group this was 10.34 (s.d. 1.71). This difference is marginally statistically significant (Wilcoxon rank sum test: $z = 1.73$, $p = 0.084$). However, the different submission times did not persist at all for subsequent tutorials: no significant differences were seen in submission times between the nudged and un-nudged students after tutorial 4.[7]

It is worth noting that since the nudged and un-nudged students were in the same class, the possibility of contagion between the groups (where the nudge communication might have been mentioned by nudged students to un-nudged students) cannot be eliminated.

4.4. Beliefs and procrastination: Research Question 4

Table 7 shows the OLS regression results, with standard errors clustered at the level of the individual student. Although there is a small positive coefficient associated with the "Beliefs Others" variable, indicating the expected value of the student's reported beliefs about the proportion of the class submitting tutorials early, this is not statistically significant. This suggests that beliefs about others' submission behaviour does not significantly predict students' own submission times. This finding helps to explain the lack of reduction in procrastination seen with the social norms nudge.

In regression (2) demographic control variables are added. In regression (3) another beliefs variable is included: in the survey questions, students were asked about their beliefs about the grades of early submitters relative to others. Options included "early submitters do much better"; "early submitters do slightly better"; "early submitters get similar grades" and "early submitters do slightly worse". The "Beliefs Grades" variable was coded as 1 for those who selected either of the options of better results for early submitters. Here too, the coefficient is not statistically significant, suggesting that believing that early submitters do better does not impact submission times.[8] Recall that the second nudge presented information about the better performance of early submitters. Again, since beliefs about the association between early submission and grades do not significantly impact submission times for this group of students, it is perhaps not surprising that the second nudge also did not reduce procrastination at the aggregate level.

Finally, in regression (4) the degree of self-reported procrastination is included. Unsurprisingly, those who claim to procrastinate more frequently also submit later, on average.

5. Discussion

In this study, the previously noted positive relationship between time to submission deadline and grade received was supported. The online assessments necessitated by the Covid-19 related lockdown in South Africa allowed this relationship to be assessed in a robust way, using a large sample of over 17,000 assessments where the exact submission time was recorded. Having multiple assessments for each individual allowed for individual fixed effects to be controlled for in regression analysis.

Part of the association between submission times and grades is likely related to early submitters typically being diligent students who might put more effort into their work. However, this study shows that the association between submission times and grades is robust to controlling for student effort in the form of joining live online lectures, listening to lecture recordings and accessing class slides. The findings show that while there is a significant positive association between engagement (particularly listening to lecture recordings) and grades, this association falls away when student fixed effects are included. This significant relationship therefore seems to describe differences between individuals.

My hope was to leverage the confirmation of a link between submission times and grades to encourage students to submit

[5] The sample size used for this experiment allowed for a minimum detectable effect of a 2% change in the log of seconds remaining. Only a 0.6% change was seen in the experiment.

[6] To see whether this difference in likelihood to submit might have impacted the results of the study, I considered an adjusted submission time measure of ln(1 +seconds to submission deadline) so that unsubmitted assignments could be included with 0 s to submission time. However, the post-nudge submission times do not differ significantly between the 2 groups even accounting for these unsubmitted tutorials: $z = 0.88$, $p = 0.38$. My thanks to an anonymous reviewer for suggesting this analysis.

[7] Wilcoxon rank-sum tests comparing submission times for each of tutorials 5–9 all had p-values over 0.5.

[8] Similar results were found where only those who believed that early submitters do much better were coded as 1.

assignments earlier. Although students with better mastery might also be early submitters, I (along with other researchers) hypothesised that at least part of the negative impact of late submission is related to underestimating the time required to complete an assignment, and running out of time. Indeed, the finding of a significant relationship between submission times and grades when accounting for student fixed effects supports the hypothesis that this relationship cannot be accounted for entirely by individual differences.

Two "nudges" were used to encourage students to submit earlier: the first was a communication about social norms relating to submission times; and the second an information nudge pointing out the average grade difference between early and late submitters. Neither of the nudges was successful in generating earlier submission times at the aggregate level. Investigation of the relationship between students' beliefs and submission times revealed that neither beliefs about others' behaviour nor beliefs about the grade impact of early submission were significant predictors of students' submission times.

Nudges do not always work: a recent meta-analysis of nudge interventions (Hummel and Maedche, 2019) finds that nearly 40% of nudges do not get statistically significant results. Another recent meta-analysis (Mertens et al., 2022) noted that nudge effectiveness varies by technique and domain. These authors also noted a moderate publication bias towards positive results.

Further, some nudge studies (e.g. Chapman and Ogden, 2012; Okeke et al., 2018; Venema et al. (2020)) suggest that habitual behaviours might be more difficult to address with nudges. For example, looking at canteen arrangements, Chapman and Ogden (2012) found that impulsive behaviours (picking up unhealthy food at checkout) were easier to address with nudges (changing the canteen layout), while habitual behaviours (white versus wholewheat bread) did not change significantly with layout alterations, as consumers would seek out their preferred bread. Since study methods are likely habitual for university students, this, together with our findings about beliefs and behaviour, might help to explain the lack of significant change noted in our study.

Finally, research by Rabb et al. (2022) highlights diminishing returns in the use of nudges to encourage vaccination among more vaccine hesitant groups. They question whether nudges can be used to change motivations among reluctant people. This might also help to explain the lack of response of students to (yet another) encouragement by a lecturer not to procrastinate too much. Perhaps nudges are less effective among those who are hesitant to change their academic behaviour.

Since the course where these nudges were tested was one that was forced to be online by the lockdowns imposed due to the Covid-19 pandemic, rather than being a course where students elected to pursue online study, one limitation of this study is that behaviour in this group might not be representative of usual student behaviour in a face-to-face course. Further research following the resumption of face-to-face teaching will investigate this.

Data Availability

Data will be made available on request.

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Declarations of interest

None.

CRediT authorship contribution statement

Nicky Nicholls: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Writing – original draft, Writing – review & editing.

Appendix A. Appendix

Robustness checks for Research Question 1

Robustness checks for the first research question are shown below. Table 8 shows a probit regression considering the probability of receiving a passing grade (50% or higher). As in the main regression, a positive relationship between earlier submission and likelihood of passing a course is seen. Table 9 reports similar findings when considering the probability of passing with distinction (75% or higher).

Table 8
Probit regression: Probability of receiving a passing grade (50% or more).

	(1)	(2)	(3)	(4)
ln(seconds until deadline)	0.134 * **	0.118 * **	0.141 * **	0.148 * **
	(0.01)	(0.01)	(0.01)	(0.01)
Age		− 0.009	− 0.084 * **	− 0.087 * **
		(0.01)	(0.01)	(0.01)
Race: Indian		0.801 * **	0.764 * **	0.798 * **
		(0.10)	(0.10)	(0.10)
Race: White		0.712 * **	0.658 * **	0.683 * **
		(0.05)	(0.05)	(0.05)
Gender: Male		0.167 * **	0.165 * **	0.168 * **
		(0.05)	(0.04)	(0.05)
Year: Second			0.583 * **	0.682 * **
			(0.07)	(0.08)
Year: Third			0.661 * **	0.774 * **
			(0.07)	(0.08)
Assessment: Mid-term				− 0.072 *
				(0.04)
Assessment: Final Exam				0.607 * **
				(0.05)
constant	0.189	0.096	1.195 * **	1.096 * **
	(0.12)	(0.30)	(0.31)	(0.32)
Observations	17241	16672	16672	16672
Log likelihood	− 6124.79	− 5779.50	− 5724.93	− 5622.69
Chi2	110.78 * **	352.00 * **	436.31 * **	722.21 * **

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

Table 9
Probit regression: probability of receiving a distinction (75% or more).

	(1)	(2)	(3)	(4)
ln(seconds until deadline)	0.059 * **	0.059 * **	0.072 * **	0.108 * **
	(0.01)	(0.01)	(0.01)	(0.01)
Age		0.088 * **	− 0.087 * **	− 0.087 * **
		(0.01)	(0.02)	(0.02)
Race: Indian		0.968 * **	0.925 * **	0.929 * **
		(0.09)	(0.09)	(0.09)
Race: White		0.710 * **	0.686 * **	0.682 * **
		(0.05)	(0.05)	(0.05)
Gender: Male		0.167 * **	0.171 * **	0.172 * **
		(0.05)	(0.04)	(0.04)
Year: Second			1.421 * **	1.552 * **
			(0.07)	(0.07)
Year: Third			1.164 * **	1.385 * **
			(0.07)	(0.07)
Assessment: Mid-term				0.131 * **
				(0.04)
Assessment: Final exam				0.404 * **
				(0.04)
constant	− 1.037 * **	− 3.207 * **	− 0.202	− 0.720 * *
	(0.10)	(0.29)	(0.32)	(0.33)
Observations	17241	16672	16672	16672
Log Likelihood	− 10181.03	− 9696.73	− 9426.55	− 9375.39
Chi2	33.87 * **	364.44 * **	912.79 * **	977.00 * **

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

Instructions for belief elicitation task

Below are some notes to explain the beliefs question in the next tab.

In the question, you are asked how many people in the EKN 244 class (as a percentage) will submit their problem sets more than 12 h before the due time. Since you might not know the exact percentage of people in the class who will do this, you will answer the question by allocating tokens to different possible percentages of people who might submit early. How you answer this question will depend on how many people you think are early submitters, and how sure you are that your estimate is correct.

You have 100 tokens that you need to allocate (the tokens represent the probability or likelihood that you believe the true percentage of early submitters falls in the range indicated). You need to allocate all tokens, so that the probability adds up to 100%.

Consider the example below. This person is certain that there are between 11% and 20% of people in the class who submit problem sets early, and has decided to put all 100 tokens in the 11–20 box. That gives them a high payment of R100 if they are correct and there are indeed between 11% and 20% of the class who submit early. However, if the true percentage of early submitters is 21% or 10% or any value outside of 11%– 20%, they would get no money:

What percentage of the EKN 244 class submitted problem sets more that 12 h before the due time?

Percent submitting early	Probability that this percentage submitted early	Payout if this is the true percentage
0–10%	0	R0
11–20%	100	R100
21–30%	0	R0
31–40%	0	R0
41–50%	0	R0
51–60%	0	R0
61–70%	0	R0
71–80%	0	R0
81–90%	0	R0
91–100%	0	R0
Total tokens allocated (you should allocate 100 tokens)		

100 DONE.

Now consider another example. This person thinks that there are probably between 21% and 30% of people who submit early, but they are not sure, and they don't want to have no money. So they have allocated quite a few tokens to the 21–30 range, but have also put a few tokens in other ranges in case they are wrong. That will mean that they get less than R100 if the true probability is in the 21–30% range (in this case, they would get R44).

But, it also means they will get some money if the true probability of early submission is in a different range (in the example below they will get R48 if the true probability is between 11% and 20% or if the true probability is between 31% and 40%; and they will get R28 for a true probability less than 10% or over 40%).

What percentage of the EKN 244 class submitted problem sets more than 12 h before the due time?

Percent submitting early	Probability that this percentage submitted early	Payout if this is the true percentage
0–10%	0	R28
11–20%	20	R48
21–30%	60	R88
31–40%	20	R48
41–50%	0	R28
51–60%	0	R28
61–70%	0	R28
71–80%	0	R28
81–90%	0	R28
91–100%	0	R28
Total tokens allocated (you should allocate 100 tokens)		

100 DONE.

How you assign your tokens is totally up to you: some people might be really confident about their estimate of the true percentage of the class who submit early; others might be less sure and want to put some tokens in different ranges. You will see, in each case, how much money you will get for each possible true percentage of early submitters. Play around with the spreadsheet a bit and you can see how the money amounts change with different probability/token choices.

Later on in the course, I will announce the true percentage of early submitters, and you will be paid based on your chosen token placement and the actual true percentage, so think about your answers please.

Please make sure you allocate all 100 tokens. The spreadsheet will tell you (in red text) if you have allocated too many or too few tokens.

Comparison between those who did and did not answer the beliefs task

Table 10.

Table 10
Beliefs task responders and non-responders.

	Responders		Non-responders	
	Mean	Std. Dev.	Mean	Std. Dev.
Age	21.14	1.64	20.98	1.72
Gender: Male	0.45		0.66	
Gender: Female	0.55		0.34	
Race: Black	0.68		0.69	
Race: Indian	0.03		0.09	
Race: White	0.27		0.22	
Grade	66.02	24.31	62.9	26.90
Time to deadline (seconds)	80,201	123,080	132,902	146,937

N = 74 responders, N = 58 non-responders

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