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Working Paper:

Never Put Off 'Till Tomorrow?

Ignacio Martinez[1]

This paper identifies the causal effect of procrastination on achievement in a MOOC. I use two approaches, instrumental variables (IV) and a randomized control trial. I show that rain and snow affect when a student takes a quiz, and therefore can be use as an IV. I find that taking the course first quiz on the day it is published, rather than procrastinating, increases the probability of course completion by 15.4 percentage points. For the randomized control trial, I send an email (directive nudge) encouraging a randomly selected group of students to procrastinate less. As an example of the magnitude of the effects, Germans assigned to the treatment group were 167% more likely to obtain the course certificate. This shows that very low-cost intervention can increase student achievement. I also find that the effects are heterogeneous across countries, suggesting that it may be advisable to customize nudges to country characteristics. This online experiment may provide valuable lessons for traditional classrooms.

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Never put off 'till tomorrow?

Ignacio Martinez

1 Introduction

Thomas Jefferson famously said, "Never put off 'till tomorrow what you can do today."[1] Conventional wisdom establishes that procrastination is bad for student achievement: without deadlines students may procrastinate on their work, and this may reduce learning.

Research on procrastination is difficult to measure and endogenous to most outcomes of interest. Most papers rely on self-reported procrastination, which may cause a Hawthorne effect: students may change their behavior and procrastinate less because they are asked to record their behavior. Also, low ability students may be more likely to procrastinate, and changing their work habits might not improve their outcomes.

Massive Online Open Courses (MOOCs) provide an ideal laboratory to study procrastination. The rich data that MOOC providers collect include when the course material is published and when the students interact with it. Therefore, researchers can observe procrastination directly without relying on self reported measures. Using data from Coursera, a MOOC provider, Martinez and Diver (2014) provide descriptive evidence of the strong negative correlation between procrastination and achievement, as shown in Figure 1: students who attempt Quiz 1 for the first time later, perform on average worse than those who do not procrastinate.

In this paper, I use two approaches to estimate the causal effect of procrastination on achievement. First, because MOOCs collect information on individual IP addresses, I can use weather data for an instrumental variables (IV) approach. Second, I use directive nudges for an experimental approach.

[1] `http://www.monticello.org/site/jefferson/canons-conduct`

Weather shocks provide a source of variation that predicts procrastination. I show that rain and snow affects when a student takes a quiz, and therefore can be use as an IV. For example, a student is 2.3 percentage points less likely to attempt the first quiz the day it is published on a day with with rainfall, but 5.0 percentage points more likely on a day with snowfall.

Next, I show that a directive nudge can affect students choices and help them improve their achievement. These results are more important than the weather IVs because they can be replicated in all types of classrooms. Students randomly assigned to the treatment group received an email in which I provide them with information about the negative correlation between procrastination and achievement. These students were 17% more likely (relative to a very low base rate) to successfully complete the course than students in the control group. Additionally, I show that the effect of the treatment is heterogeneous among different countries. For example, Germans assigned to the treatment group were 167% more likely to obtain the course certificate, Spaniards 67%, and Indians 40%.

The remainder of this paper is organized as follows. In the next section, I discuss the relevant literature. In Section 3, I present the economic model. Section 4, describes the data. In Section 5, I show that weather can be use as an instrument. Section 6, describes the randomized control trial and its results. In Section 7, I conclude.

2 Literature

Psychologists have been studying procrastination since the seventies. Ellis and Knaus (1977) claim that, "Procrastination constitutes an emotional hang-up that does you considerable damage." They also claim that, based on their work as psychotherapists, about ninety-five percent of college-level individuals procrastinate. They never consider that they are basing their "guesstimate" from a highly selected sample (i.e., their patients). Neither did they consider that procrastination could be correlated with some other un-

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observed characteristic which is the real cause for their patients problems. Knaus (2001) describe procrastination as our "ancient nemesis". He claims procrastination may have originated as early as 2.5 million years ago when our ancestors first grouped into small clans and someone decided to needlessly put off doing something beneficial for the clan. These hypotheses are founded with small surveys that rely on indirect measures of procrastination. Moreover, none of these studies addresses the problem of procrastination being an endogenous choice. Chun Chu and Choi (2005) are the first to consider that "active" procrastination could be good: some people choose to procrastinate because they know they will do better under pressure. For their study, they invited students to respond to a questionnaire entitled "Survey of University Students' Time Use." 230 undergraduate students filled out the questionnaire, but the paper does not mention how these students compared to their peers who chose not to participate in the study. This raises concerns about selection bias and external validity. In this paper, I use a direct measure of procrastination and both an instrumental variable and experimental approach to deal with the endogeneity concerns.

The first paper to address procrastination in the economic literature is Akerlof (1991). Akerlof argues that although procrastination might initially appear to be outside the appropriate scope of economics, it affects the performance of individuals and institutions in the economics and social domain. He proposes an economic model in which procrastination occurs when present costs are unduly salient in comparison with future costs, leading individuals to postpone tasks until tomorrow without foreseeing that when tomorrow comes, the required action will be delayed yet again. This model challenges the common assumption in economics that individuals are rational maximisers. Anderson and Block (1995) argues that the examples Akerlof offers can be explained within the framework of the standard economic model. They argue that Akerlof confuses later regret with prior irrationality, which is parallel to confusing ex post with ex ante. O'Donoghue and Rabin (2001) develop a model where a person chooses from a menu of options and is partially aware of her self-control problems. Their model predicts that additional options can induce procrastination, and a person may procrastinate more in pursuing important goals than unimportant ones. They argue that their second result arises because the greater the effort a person intends to incur, the more likely she is to procrastinate in executing those plans. Instead of using the standard economic assumption that preferences are time-consistent (i.e., a person's relative preference for well-being at an earlier date over a later date is the same no matter when she is asked), they model individuals with present-biased preferences. Finally, Siegfried (2001) argues that combating procrastination is essential in order to have a successful undergraduate economics honors program. He argues that getting students to work on their thesis early is the key to success. In order to achieve this his university uses a series of short-term deadlines and the "fear of personal embarrassment"

One approach that I use to control for the endogeneity of procrastination is to use weather as an instrument. The method of instrumental variables is a signature technique in the econometrics toolkit, as discussed in Angrist and Krueger (2001). Connolly (2008) links the American Time Use Survey to rain data from the National Climatic Data Center (NCDC). She finds that, on rainy days, men shift on average 30 minutes from leisure to work, suggesting that rain raises the marginal value of work. In this paper, I link data from the NCDC on rain and snowfall to data from Coursera. Coursera collects student's IP addresses. Using this, I geolocate students and assign them a NCDC weather station. Assuming that procrastinators do not choose their location in response to the weather, rain and snow are an exogenous source of variation for procrastination and allows me to identify the causal effect of procrastination on achievement.

MOOCs offer a new learning environment. Martinez and Diver (2014) explore the opportunities and challenges that MOOCs generate for research. Using data from Coursera, they show a strong negative correlation between procrastination and achievement. In this paper, I go beyond studying the correlation to determine the causal effect of procrastination on achievement by using both an instrument variables and experimental approach. The experimental approach consists of nudging students by sending information in a email, as in Martinez (2014). The term "nudge" was first used by Thaler and Sunstein (2008) to describe "Any aspect of the choice architecture that alters people's behavior in a predictable way without forbidding any option or significantly changing their economic incentives."

3 Model

In this section, I present a simple model in which a student with ability a chooses whether to take a Quiz in the first period, procrastinate and take it in the second, or not take it at all.[2] In the second period, if the student's best grade is greater than $\overline{g}$, the student gets a payoff equal to W. Not attempting the Quiz in a given period yields a grade equal to zero. On the other hand, attempting the Quiz yields an uncertain grade determined by a function of his ability and an unobserved random variable ϵ_t:

$$g_t = f(a, \epsilon_t).$$

Each period the student gets utility from non-Coursera activities (i.e., leisure, and work), ℓ_t. The marginal utility of these activities is given by μ_t. If students like to procrastinate, $\mu_1 > \mu_2$.

The utility of attempting the Quiz in period 2 for a student with a grade from period 1 equal to g_1 and ability a is given by the utility from non-Coursera activities when attempting the quiz, plus the expected payoff of succeeding in the course:

$$V_2^T(g_1, a) = \mu_2 \ell_{2,T} + \Pr\left[\max(g_1, g_2) > \overline{g} \middle| a\right] W.$$

[2]In this model, the student is rational and has time consistent preferences. The student will choose to procrastinate if that is the optimal choice given his information set. An alternative model could generate procrastination by assuming agents with time inconsistent preferences, as in Choi et al. (2003).

The utility of not attempting the quiz in period 2 for a student with grade from period 1 equal to g_1 and ability a is given by the utility from non-Coursera activities when not attempting the quiz, plus the payoff of succeeding in the course if the grade in period 1 was greater than the threshold:

$$V_2^{NT}(g_1) = \mu_2 \ell_{2,N} + \mathbb{1}_{(g_1 > \overline{g})} W.$$

Therefore, the period 2 problem can be written as:

$$V_2(g_1, a) = \max\left\{V_2^T,\, V_2^{NT}\right\}.$$

The period 1 problem, in which the student decides whether to attempt the quiz or procrastinate, can be written as:

$$V_1(a) = \max\left\{\mu_1 \ell_{1,N} + E\left[V_2(0,a)\right],\, \mu_1 \ell_{1,T} + E\left[V_2(g_1,a)\right]\right\},$$

where grades are a function of student ability and an unexpected shock, and the utility from non-Coursera activities is greater when non attempting the quiz:

$$g_t = f(a, \epsilon_t)$$

$$\ell_{t,N} > \ell_{t,T}$$

This problem can be easily solved recursively. A student with $g_1 > \overline{g}$ will not attempt the quiz in period 2.[3] A student with $g_1 < \overline{g}$ will attempt the quiz if

$$\Pr\left[g_2 > \overline{g}\right] W > \mu_2 \left(\ell_{2,N} - \ell_{2,T}\right)$$

[3]Adding direct utility from grades would allow this model to explain students attempting the quiz eventhough they do not need to do it in order to obtain W.

In the first period, a student will attempt the quiz if

$$\mu_1 \ell_{1,T} + E\left[V_2\left(g_1, a\right)\right] > \mu_1 \ell_{1,N} + E\left[V_2\left(0, a\right)\right]$$

$$E\left[V_2\left(g_1, a\right)\right] - E\left[V_2\left(0, a\right)\right] > \mu_1\left(\ell_{1,N} - \mu_1 \ell_{1,T}\right)$$

If the expected value of attempting the Quiz in period 1 increases, $\uparrow E\left[V_2\left(g_1, a\right)\right]$, or the expected value of going into period 2 with a grade of zero decreases, $\downarrow E\left[V_2\left(0, a\right)\right]$, then students who were at the margin of attempting the Quiz in period 1 will take it, that is, they will procrastinate less. We can interpret the empirical strategies which I employ in terms of changes in key parameters in the model.

The intention of the informational experiment described in section 6 is to increase the expected value of attempting quizzes earlier. Similarly, if the marginal utility of non-Coursera activities decreases, $\downarrow \mu_1$, students at the margin will procrastinate less. In section 5, I show that rain and snow affect procrastination.

4 Data

I use data from two sources. The first is Coursera, an education platform that partners with top universities and organizations worldwide to offer free online courses to anyone. The second source, is the National Climatic Data Center (NCDC) of the National Oceanic and Atmospheric Administration (NOAA).[4] Coursera data provides me with a measure of procrastination, and a platform to run an experiment. I link these data with NCDC data which provides weather conditions (rain and snow) for each Coursera participant in the geography identified by IP addresses.

[4] This weather data is publicly available at `http://goo.gl/x2UrXq`.

4.1 Coursera

I use data from the third edition of Foundations of Business Strategy (FBS) by Michael J. Lenox of the University of Virginia. 75,180 students were initially enrolled in this course. The course ran from January 13, 2014 to February 25, 2014. FBS. explores the underlying theory and frameworks that provide the foundations of a successful business strategy. The class is divided into weekly modules. Each module consists of an introductory video, a reading from the strategist's toolkit, a series of video lectures, a quiz, and a case study to illustrate points in the lectures. Students wishing to receive a Statement of Accomplishment must satisfy the following criteria:

1. Complete the 6 quizzes. Students can take each quiz three times. The recorded score is the best score on each quiz. Quizzes have 10 questions with 4 choices each.
2. Submit a final project: a strategic analysis for an organization of their choosing.
3. Assess five peers' strategic analysis using the peer assignment function.

Final grades are out of 100 points. Out of the 100 points of the final grade, 50 points are for the final project, 42 points for the quizzes (spread evenly over the 6 quizzes), and 8 points for post and comment up-votes. Those who receive 70 points or more and assess five peers' strategic analysis receive a Statement of Accomplishment.

In this paper I use the 24,122 students who expressed, at the time of enrollment, their intention to complete all the course work necessary to obtain the Statement of Accomplishment.[5] These students were randomly assigned to treatment and control groups to test whether a directive nudge affects their behavior and achievement. Only 1,212 of these students received a Statement of Accomplishment.

[5]At the time of enrollment students had to answer the following question: "How many of the assignments and quizzes do you intend to do?" Only students who selected all were considered for this study. Other students may have little or no intention of taking the quizzes.

Figure 2 shows when each of the quizzes were published, and the timing of the directive nudge intervention, which occurred on the same day that Quiz 6 was published.

4.2 Weather Data

The NCDC has data from more than 90,000 weather stations around the world.[6] The data includes maximum and minimum daily temperatures, rain, and snowfall. Using stations and students, latitude and longitude, I can match each student to their nearest weather station.

Connolly (2008) shows that, for men, a rainy day shifts about half an hour from leisure and home production to work, suggesting that rain raises the marginal value of work.[7] As in her paper, I define a rainy day as a day with at least 0.10 inches of rain. Additionally, I take snow into consideration, and I define a snowy day as a day with at least 0.10 inches of snow. Rain and snow might have different effects on student choices. For example, in a rainy day a student may stay at work until later and be less likely to do Coursera work when he gets home. On the other hand, on a snowy day a student may have to stay home instead of going to work, increasing the likelihood of doing Coursera work.

5 The Effect of Procrastination Using Weather as an Instrument

I estimate linear regressions using rain and snow as IVs for procrastination. The course started on Monday January 13, and the first quiz was published that day, (Figure 2). The OLS estimate in the first column of Table 1 shows that a student who takes

[6] In this paper I use their daily data, but it is possible to access hourly records

[7] Result for women are weak. A rainy day is associated with 3 more minutes at work.

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the Quiz on day 1 is 15.4 percentage points more likely to obtain the statement of accomplishment than a student who does not, relative to a very low base of 0.6% who obtain the statement.

If procrastination is correlated with some other unobserved characteristic (e.g., ability), this estimate would be biased, probably upward. To deal with this endogeneity bias, I estimate a first stage relationship that shows that a student is 2.3 percentage points less likely to take the Quiz on the first day if it is raining, and 5 percentage points more likely if it is snowing. Connolly (2008) suggests that on a rainy day people are more likely to spend more time at work. If this is so, they would have less time to do their Coursera activities. On the other hand, on a snowy day people are more likely to stay home and do their Coursera work.

The second stage regression shows that being induced not to procrastinate in take the Quiz on day one increases the probability of obtaining the statement of accomplishment by 13.8 percentage points. Thus, the estimate shrinks because some good students self-select.[8]

I can further investigate the impact of procrastination by consider how long it takes a student to attempt the quiz, rather than simply looking at whether they take it on the first day. However, I cannot observe this measure of procrastination for students who never took the Quiz. In order to have another estimate of the effects of procrastination on achievement I define an upper and lower bound for those students who did not take the Quiz. In Table 2, I assume that students who did not take the Quiz would have pro-

[8]Note that Table 1 uses a linear probability model. Wooldridge (2012) says "...the linear probability model is useful and often applied in economics. It usually works well for values of the independent variables that are near the average in the sample". Angrist and Pischke (2008) give several empirical examples where the marginal effects of a dummy variable estimated by LPM and probit are indistinguishable. IV Probit can not be used here because the endogenous regressor is discrete. Vytlacil and Yildiz (2007) propose nonparametric identification and estimation of the average effect of a dummy endogenous regressor in models where the regressors are weakly but not additively separable from the error term. A dynamic discrete choice model with 41 periods and new choices appearing every week could be a better specification. But that specification is more costly to solve and does not provide any clear advantage over this simple specification.

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crastinated until one minute after the deadline. In Table 3, I assume that students would have procrastinated for a year after the deadline. The IV estimate using the lower bound implies that an additional hour (week) of procrastination decreases the probability of obtaining the certificate by 0.01 (1.68) percentage points. The upper bound assumption, implies that a week of procrastination decreases the probability of obtaining the certificate by 0.336 percentage points. The fact that these estimates for procrastination are much smaller than the estimate from Table 1 shows that the effects of procrastination are non-linear. That is, procrastinating the day the Quiz is published has much larger effects than procrastinating an additional day after 10 days of procrastination.

6 Randomized Email Nudge

I divided up the group of 24,122 students into randomly assigned treatment and control groups. On February 17, 2014, the day Quiz 6 was published, I sent an email to the students in the treatment group, as shown in Figure 3. This email is a low-cost directive nudge encouraging students not to procrastinate.[9]

Table 4 shows the effect of the treatment on Quiz 6 outcomes. In order to deal with attrition, I assign a grade of 0 to students who did not attempt the quiz. "Took Q6" shows that students in the treatment group were 0.8 percentage points, or 7.74%, more likely to take the quiz. "maxGrade" shows that students assigned to the treatment group scored 7 points, or 8.92% better on their best attempt on Quiz 6 than students in the control group. "Procrastination" suggests that, conditional on taking the quiz at some point, students assigned to the treatment group procrastinated 2.1 fewer hours on average. This difference is not statistically significant.

[9] I can confirm that 43.02% of these emails were open. To know this, a unique white pixel is inserted in the body of the email. When the white pixel loaded from the server, I know the email was open. Because images are blocked by default on some email clients, these numbers are lower bounds for the open rates. The open rate is crucial to calculating the effect of the treatment on the treated.

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The nudge not only affected students' behavior in Quiz 6, but also their choices to go back and take quizzes 1 to 5 for the first time. For example, Table 5 shows that students receiving the email nudge were about a half percentage point more likely to attempt Quizzes 1-5 for the first time after the intervention than students in the control group. The students who were nudged into taking the quizzes are increasing my measure of procrastination in the treatment group.[10]

Students assigned to the treatment group were not only more likely to complete Quiz 6, but also to obtain a Statement of Accomplishment. Table 6 shows that students assigned to the treatment group were 0.8 percentage points, or 16.85% more likely to obtain the course certificate. For an intervention with negligible cost, this is an important effect.

Table 7 shows that the treatment has heterogeneous effects across countries. Italians assigned to the treatment group procrastinated, on average, 63.22 fewer hours than those assigned to the control group. Nigerians and Indians assigned to the treatment group procrastinated more than those in the control group. This is explained by the fact that those assigned to the treatment group still procrastinated but were more likely to take the quiz at all.

Finally, Table 8 shows that the effect on outcomes is also heterogeneous across countries. Germans assigned to the treatment group were 167% more likely to obtain the certificate, Spaniards 67%, Indians 40%, and there were not statistically significant effects for other countries.

[10] For example, imagine that there are only 2 students in the treatment and 2 in the control group. One student in each group took Quiz 1 before the intervention. After the intervention, the student in the treatment group decides to stop procrastinating and take the Quiz, but the student in the control group keeps on procrastinating. This will increase my measure of procrastination for the treatment group.

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7 Conclusions

This paper examines the role of procrastination on achievement. Understanding whether or not there is a causal relationship, so that inducing procrastinators to take action improves their learning, is fundamental in order to design a course with incentives that maximize student achievement.

First, I show that a student is less likely to take a quiz on a rainy day and more likely to take a quiz on a snowy day. Using weather as an instrument, I show that attempting the first quiz on the day it is published increases the probability of obtaining the Statement of Accomplishment by 13.8 percentage points.

Second, I show that a directive nudge can strongly increase achievement. For example, students in the treatment group were 0.8 percentage points, or 16.85% more likely to obtain the course certificate. For an intervention with negligible cost, this is an important effect. Moreover, the effects are heterogeneous across countries. For example, Germans assigned to the treatment group were 167% more likely to obtain the course certificate, Spaniards 67%, and Indians 40%. There were no statistically significant effects in achievement for students from other parts of the world, especially as sample sizes got smaller. In order to understand the causes of this heterogeneity, more data is needed. For example, it is possible that the level of education are different, or employment status, or simply cultural differences. Currently, Coursera survey data is not good enough to address this question, but Coursera is constantly improving their platform.

Future research should explore other directive nudges to improve achievement. For example, evidence Martinez (2014) shows that telling students how they are performing relative to their peers can improve ranking, on average, by 8.43 percentage points. Future intervention could test what is the impact of telling students how students in the top of the class are using their time before attempting a quiz.

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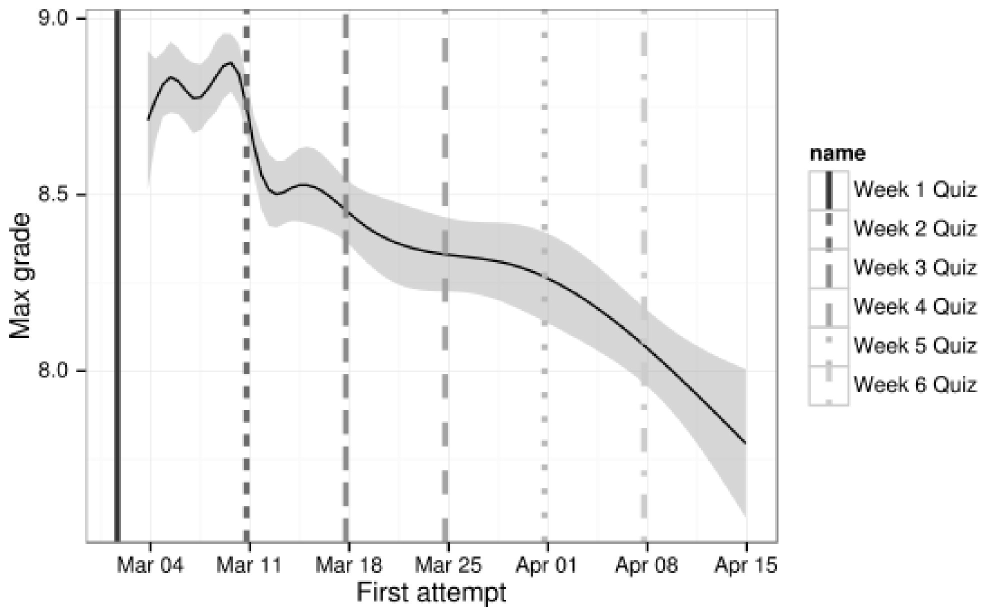
Figure 1: Procrastination and Achievement



Note: Extracted from Martinez and Diver (2014).

Figure 2: Time Line

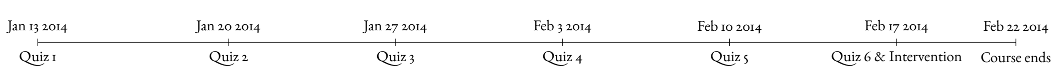
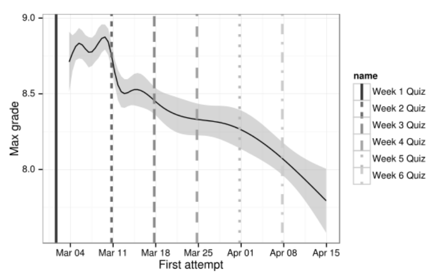


Figure 3: Treatment

Subject: [Foundations of Business Strategy] Don't Leave for Tomorrow What You Can Do Today

Dear [name],

Our analysis of the previous iteration of this course shows that students who choose to do the quizzes late perform worse than those who do them earlier.



We encourage you to try the next quiz earlier. Keep in mind that you can retake the quizzes 3 times.

Best,

University of Virginia MOOC Research Team

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Table 1: Regression Results, taking Quiz 1 the day is published and achievement

	Dependent variable:		
	Certificate	took Quiz 1 the 13	Certificate
	OLS	First Stage	Second Stage
	(1)	(2)	(3)
took Quiz 1 the 13	0.154***		0.138**
	(0.003)		(0.063)
rain the 13[a]		−0.023***	
		(0.006)	
snow the 13[b]		0.050**	
		(0.020)	
longitude		−0.0002***	
		(0.00004)	
Constant	0.006***	0.291***	0.011
	(0.002)	(0.004)	(0.018)
Observations	23,463	23,463	23,463
R^2	0.102	0.002	0.101
Adjusted R^2	0.102	0.002	0.101
Residual Std. Error	0.206 (df = 23461)	0.451 (df = 23459)	0.206 (df = 23461)
F Statistic	2,678.940*** (df = 1; 23461)	17.446*** (df = 3; 23459)	

Notes: *p<0.1; **p<0.05; ***p<0.01
[a] dummy variable equal to 1 if it rained more than 0.1 inches the day Quiz 1 was published.
[b] dummy variable equal to 1 if it snowed more than 0.1 inches the day Quiz 1 was published.

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Table 2: Regression Results, Procrastination Q1 and Achivement

	Dependent variable:		
	Certificate	ProcrastinationLow	Certificate
	OLS	First Stage	Second Stage
	(1)	(2)	(3)
ProcrastinationLow[a]	-0.0002^{***}		-0.0001^{**}
	(0.00000)		(0.0001)
rain the 13[b]		18.949^{***}	
		(5.243)	
snow the 13[c]		-46.341^{***}	
		(17.248)	
longitude		0.220^{***}	
		(0.034)	
Constant	0.196^{***}	816.126^{***}	0.160^{***}
	(0.003)	(3.266)	(0.055)
Observations	23,463	23,463	23,463
R^2	0.102	0.003	0.096
Adjusted R^2	0.102	0.003	0.096
Residual Std. Error	0.206 (df = 23461)	389.703 (df = 23459)	0.207 (df = 23461)
F Statistic	$2,676.202^{***}$ (df = 1; 23461)	20.741^{***} (df = 3; 23459)	

Notes: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

[a] how many hours pass between the publishing of the Quiz and their first attempt at it. For students who did not attempt the Quiz, I assume they procrastinated until a minute after the deadline.

[b] dummy variable equal to 1 if it rained more than 0.1 inches the day Quiz 1 was published.

[c] dummy variable equal to 1 if it snowed more than 0.1 inches the day Quiz 1 was published.

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Table 3: Regression Results, Procrastination Q1 and Achivement

	Dependent variable:		
	Certificate	ProcrastinationHigh	Certificate
	OLS	First Stage	Second Stage
	(1)	(2)	(3)
ProcrastinationHigh[a]	-0.00002^{***}		-0.00002^{**}
	(0.00000)		(0.00001)
rain the 13[b]		243.716^{***}	
		(57.891)	
snow the 13[c]		-457.968^{**}	
		(190.432)	
longitude		2.023^{***}	
		(0.374)	
Constant	0.167^{***}	$6,673.100^{***}$	0.153^{***}
	(0.002)	(36.055)	(0.044)
Observations	23,463	23,463	23,463
R^2	0.118	0.002	0.116
Adjusted R^2	0.118	0.002	0.116
Residual Std. Error	0.204 (df = 23461)	4,302.763 (df = 23459)	0.204 (df = 23461)
F Statistic	$3{,}138.606^{***}$ (df = 1; 23461)	17.307^{***} (df = 3; 23459)	

Notes: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

[a] how many hours pass between the publishing of the Quiz and their first attempt at it. For students who did not attempt the Quiz, I assume they procrastinated for a year.

[b] dummy variable equal to 1 if it rained more than 0.1 inches the day Quiz 1 was published.

[c] dummy variable equal to 1 if it snowed more than 0.1 inches the day Quiz 1 was published.

Table 4: Quiz 6

	Treatment	Control	90% Confidence Interval	p-value
maxGrade	0.8506	0.7809	(0.0154, 0.124)	0.0347
firstGrade	0.5278	0.4966	(-0.005, 0.0673)	0.1561
Attempts	0.2461	0.2241	(0.0059, 0.0381)	0.0247
Took Q6	0.1002	0.093	(0.001, 0.0135)	0.058
Procrastination	102.9237	105.0334	(-6.8086, 2.5892)	0.4601
n	12061	12061		

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Table 5: Attempting Quizzes 1-5

	Treatment	Control	90% Confidence Interval	p-value
Quiz 1	0.0198	0.017	(0, 0.0057)	0.1034
Quiz 2	0.0273	0.024	(0, 0.0067)	0.1031
Quiz 3	0.0343	0.0296	(0.001, 0.0085)	0.0369
Quiz 4	0.0424	0.0383	(-1e-04, 0.0082)	0.1088
Quiz 5	0.0585	0.0522	(0.0015, 0.0111)	0.0323
n	12061	12061		

Table 6: Achievement

	Treatment	Control	90% Confidence Interval	p-value
Certificate	0.0541	0.0463	(0.0032, 0.0124)	0.0056
n	12061	12061		

Table 7: Procrastination by Country

Country	treatment	control	90% Confidence Interval	p-value	n Treatment	n Control
Italy	62.95	126.17	(-96.4735, -29.9799)	0.00	61	53
Nigeria	115.57	87.28	(7.753, 48.8257)	0.03	79	65
India	117.28	103.78	(1.7414, 25.258)	0.06	215	194
Mexico	112.27	150.03	(-70.4457, -5.074)	0.06	63	55
Netherlands	57.34	94.35	(-73.2042, -0.8067)	0.09	58	63
Portugal	113.85	66.98	(-1.1174, 94.861)	0.11	59	53
Canada	97.89	117.06	(-41.7352, 3.3982)	0.16	102	82
United States	99.96	107.54	(-17.3334, 2.1589)	0.20	316	314
Australia	97.61	81.27	(-11.7926, 44.4721)	0.33	74	59
Russia	89.41	114.47	(-68.7584, 18.6417)	0.34	58	62
United Kingdom	97.72	114.48	(-47.8758, 14.3557)	0.37	90	78
China	82.74	96.13	(-45.1692, 18.3865)	0.48	62	60
Spain	95.39	85.30	(-15.8501, 36.0327)	0.52	90	78
Colombia	88.31	100.23	(-58.5295, 34.6981)	0.66	56	57
France	104.11	97.24	(-19.9504, 33.6842)	0.67	76	70
Germany	100.89	95.85	(-26.5307, 36.6173)	0.79	69	54
Ukraine	82.34	87.62	(-47.6962, 37.1344)	0.83	58	54
Brazil	113.93	112.98	(-14.9745, 16.8918)	0.92	123	110

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Table 8: Course completion

Country	treatment	control	90% Confidence Interval	p-value	n Treatment	n Control
India	0.07	0.05	(0.0041, 0.0338)	0.04	1749	1677
Germany	0.08	0.03	(0.01, 0.0954)	0.04	482	506
Spain	0.10	0.06	(0.004, 0.0788)	0.07	615	602
Portugal	0.06	0.03	(-0.0089, 0.0769)	0.19	455	455
Brazil	0.04	0.03	(-0.0027, 0.0233)	0.19	1334	1336
France	0.10	0.08	(-0.0242, 0.0754)	0.40	509	506
Nigeria	0.08	0.06	(-0.0211, 0.0601)	0.43	545	521
Netherlands	0.08	0.11	(-0.0889, 0.0362)	0.49	450	437
Canada	0.09	0.08	(-0.0206, 0.0443)	0.55	725	697
Russia	0.03	0.04	(-0.0378, 0.0177)	0.55	584	559
United Kingdom	0.05	0.04	(-0.0149, 0.0291)	0.60	784	827
Italy	0.07	0.06	(-0.0366, 0.0667)	0.63	453	440
Ukraine	0.04	0.03	(-0.0231, 0.0414)	0.64	508	485
Colombia	0.04	0.05	(-0.0574, 0.0322)	0.64	448	446
Mexico	0.03	0.02	(-0.0204, 0.0336)	0.69	499	538
Australia	0.06	0.05	(-0.0275, 0.0418)	0.73	598	528
China	0.03	0.03	(-0.0182, 0.0261)	0.77	627	623
United States	0.05	0.05	(-0.0088, 0.0096)	0.94	3226	3200

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