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D is for Dillydally?

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Abstract

Evidence from online assignments in an intermediate microeconomics course suggests that non-procrastinators (both early-starters and front-loaders) score higher than their dilly-dallying counterparts. Students who are busier in school tend to start their assignments earlier.

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"D" is for Dilly-dally?

1 Introduction

"Sagacious" advice must be both logical and persistent. When available, empirical evidence must also support it. Like most advice, "Stop dilly-dallying!" has passed the first two of these tests. Dilly-dallying indeed steals time, and advice against it is persistent among parents and professors. However, because of our inability to accurately measure the degree to which procrastinators dilly-dally, we have, until recently, been precluded from empirically testing the advice. Thanks to new internet-based course-management tools, measuring procrastination among college students has become possible. We report findings from one such system, Aplia (www.aplia.com).[1] All else equal, early starters and front-loaders score higher on their assignments, i.e., there is a cost associated with procrastination.[2]

2 Aplia and Measures of Procrastination

Students registered with Aplia at the beginning of the semester to obtain nine weekly practice (i.e., ungraded) and graded assignments each.[3] The graded assignments for each topic were automatically graded at the end of the week in which they were due. Students were able to access the problems at any time during the week, in any order, and as many times as desired prior to the grading deadline. Aplia kept track of the dates and times that students first accessed each problem.

Definitions and summary statistics for our data are provided in Table 1. The first four variables were compiled by Aplia, the next two (GPA and CREDITS) are from official student transcripts, and the remaining five were obtained via an end-of-semester survey.[4] START and SKEW distinguish two types of procrastinators. START measures the time

difference (in days) between the an assignment's grading deadline and when the student first accessed the assignment to answer a question. Students with relatively high (low) START values are considered early-(late-)starters. SKEW measures skewness in the distribution of a student's time differences (in minutes) between the grading deadline and when the student first accessed each question contained in a given assignment. It represents the degree to which a student front-loads or back-loads their start times across all questions of a given assignment. Students with negative (positive) SKEWs are considered front-(back-)loaders.[5]

3   Empirical Model and Results

We begin by testing for fixed and random effects using a standard panel-data model (Greene, 2003), henceforth "standard model":

$$y_{jk} = \mathbf{x'_{jk}}\boldsymbol{\beta} + v_{jk} \qquad j = 1, \ldots, J, \quad k = 1, \ldots, K \qquad (1)$$

where y_{jk} is the SCORE for student j on assignment k, $\mathbf{x'_{jk}}$ a vector of assignment-variant and assignment-invariant explanatory variables from Table 1, and $\boldsymbol{\beta}$ a corresponding coefficient vector. The expression for v_{jk} depends on whether pooled OLS, fixed, or random effects are assumed. For pooled OLS, $v_{jk} = \alpha + \varepsilon_{jk}$, where α is a common intercept term across all students and assignments and ε_{jk} an i.i.d. error term with constant variance. For fixed effects (FE), $v_{jk} = \alpha_j + \varepsilon_{jk}$, where α_j is a student-specific intercept term. For random effects (RE), $v_{jk} = \alpha + u_j + \varepsilon_{jk}$, where u_j is a student-specific random element, similar to ε_{jk}, except that for each student a single draw enters the regression identically for each assignment.

Since START may be endogenously determined, we employ Baltagi's (2001) method to test for bias. Our focus on START as a potential endogenous covariate, rather than

SKEW, is based on separate panel regressions run to explain START and SKEW. These models indicate that variation in START across students and assignments can be explained by several of the explanatory variables contained in (1), while variation in SKEW cannot. Following Baltagi (2001), an instrumental-variables model (IV) adjusts the standard model:

$$y_{jk} = \mathbf{w'_{jk}}\boldsymbol{\gamma} + \mathbf{x'_{jk}}\boldsymbol{\beta} + v_{jk} \qquad j = 1, \dots, J, \quad k = 1, \dots, K \qquad (2)$$

where $\mathbf{x'_{jk}}$ now represents a vector of *exogenously* determined explanatory variables; $\mathbf{w'_{jk}}$ a vector of *endogenously* determined explanatory variables assumed to be correlated with ε_{jk} (in our case START); and $\boldsymbol{\gamma}$ a corresponding coefficient vector. Let the dimension for $\boldsymbol{\gamma}$ be $1 \times I_w$ (in our case $I_w = 1$), and assume a $1 \times I_z$ vector of observations on I_z instruments in $\mathbf{z'_{jk}}$ (in our case the instruments are CREDITS, CHILD, S1, and S2). The order condition $I_z \geq I_w$ is therefore satisfied, and (2) can be estimated with $\mathbf{z'_{jk}}$ in place of $\mathbf{w'_{jk}}$.

Results for various specifications of the standard and IV models are presented in Table 2.[6] Based on reported significance levels for the Breusch and Pagan (1980) LM and Hausman (1978) χ^2 specification tests for the standard model, and on the Hausman test for the IV model, we focus on results for the RE models - RE and RE(IV).[7] Since the results for these two models are qualitatively similar, we base the following interpretations on the RE(IV) model.

First, note that early-starters fare better than late-starters. For each day that a student accesses an assignment before the deadline, their score increases by approximately 2.7 percentage points, all else equal. Therefore, the greatest possible difference in score between early and late starters, ceteris paribus, is approximately 14 percentage points, or a full grade and a half per assignment. This could potentially have a large impact on a

student's overall course grade if homework assignments are a relatively large determinant of the overall course grade (in this course, homework scores accounted for 35 percent of the total grade). Front-loaders add an average of 1.85 percentage points to a given assignment. Procrastinators, both late-starters and back-loaders, therefore tend to perform worse on graded assignments than their non-dilly-dallying counterparts.[8,9]

Recent work offers compelling interpretations of both rational and irrational procrastination. Fischer (2001) models leisure as a rational exhaustible resource problem. Akerlof (1991) depicts procrastination as a response to misperceived "salience costs" that inflate the cost of current opportunities and reduce the cost of procrastinating on future tasks. O'Donoghue and Rabin (2001) differentiate between naïve and sophisticated procrastinators and introduce a menu of tasks on which an individual might choose to procrastinate. A common implication is that the relationship between the number of tasks facing the individual and the degree to which he procrastinates on any given task is (positively) monotonic. We tested this "monotonic-procrastination" hypothesis for late-starting students and found that enrolling for an additional credit hour induces an *increase* in start time by 0.12 days. This suggests a *negative* monotonic relationship between the number of tasks a student undertakes at school and late-starting procrastination.[10]

4 Conclusions

Using information from online assignments, we find evidence suggesting that non-procrastinators obtain higher scores than their dilly-dallying counterparts. This is true for both early-starters and front-loaders, although the magnitude of the early-starting effect on student performance is larger and more statistically significant. Taken together, these results suggest that the admonishment "Stop dilly-dallying!" is indeed sage advice - dilly-dallying comes with a cost. With respect to informing policy, our results suggest

that universities should not necessarily be too concerned about the effects of credit-hour loads on student procrastination habits. Although the use of internet-based assignments may still be considered pedagogically non-traditional, the course in thus study followed a traditional lecture format with reliance on homework assignments and in-class examinations to evaluate student performance, suggesting that our estimates of the effects of procrastination are generalizable to other economics and non-economics courses.

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Table 1: Variable Definitions

Variable	Description	Mean (SD)*
SCORE	Percentage correct per graded assignment.	69.89 (31.43)
PRACTICE	1 = attempted practice assignment, 0 otherwise.	0.57 (0.50)
START	Time difference (in days) between the grading deadline and first assignment access.	2.13 (2.46)
SKEW	Skewness (in minutes).	0.23 (1.08)
GPA	Grade point average (4.00 scale).	3.39 (0.35)
CREDITS	Total credits enrolled.	11.78 (3.80)
GENDER	1 = male, 0 = female.	0.70 (0.46)
HRSWORK	Total number of hours worked per week at wage-paying job.	18.27 (15.88)
CHILD	1 = at least one child under the age of 18 at home, 0 otherwise.	0.13 (0.34)
S1	1 = assignment occurred in first third of semester, 0 otherwise.	0.33 (0.47)
S2	1 = assignment occurred in second third of semester, 0 otherwise.	0.33 (0.47)

* Overall means (Mean) and associated standard deviations (SDs). Sample size for each variable is 207, except for GPA, CREDITS, and HRSWORK, which are 198 each.

Table 2: Effect of Procrastination on Score

Explanatory Variables	OLS	Fixed Effects (FE)[a]	Random Effects (RE)	RE(IV)
CONSTANT	16.82	70.39***	13.32	7.10
	(14.24)	(2.79)	(22.71)	(21.67)
PRACTICE	3.70	7.87***	6.31**	7.14**
	(2.83)	(3.03)	(3.05)	(2.97)
START	2.23***	1.81***	2.14***	2.65***
	(0.61)	(0.55)	(0.60)	(1.08)
SKEW	-1.62	-1.78*	-1.74	-1.85*
	(1.18)	(1.07)	(1.14)	(1.12)
GPA	19.82***		20.56***	20.81***
	(3.92)		(6.42)	(6.29)
CREDITS	-0.24		-0.23	
	(0.38)		(0.59)	
HRSWORK	-0.43***		-0.45***	-0.54***
	(0.10)		(0.15)	(0.13)
CHILD	-1.02		-9.06	
	(4.76)		(7.34)	
S1	1.02	0.40	0.59	
	(3.64)	(3.16)	(3.42)	
S2	-2.87	-3.06	-3.06	
	(3.42)	(2.93)	(3.19)	
$F(k, n-k)$	13.34***	5.37***		
Wald $\chi^2(k=7)$			63.77***	49.68***
Adjusted R^2	0.39	0.09	0.42	0.39
LM χ^2			8.15***	
Hausman χ^2		2.03		1.14

Standard errors in parentheses. Number of observations is 175 for each regression, except for FE, which is

184. *** Significant at 1% level, ** Significant at 5% level, * Significant at 10% level.

[a] Standard errors corrected using Cornwell, et al.'s (1992) method.

Notes

1. The closest studies to ours concerning the factors influencing student performance in economics are Johnson et al. (2002) and Krohn and O'Connor (2004), but these deal with measures of effort rather than delay.

2. What a professor perceives as dilly-dallying may instead be the optimal outcome of the student's time-allocation problem. In this case, the cost incurred is that of optimal rather than abject dilly-dallying. To distinguish empirically between the two would require an underlying general equilibrium model of student choice.

3. The assignments were advanced 'workouts' in Bergstrom and Varian (2003). The course text was Varian (2003). Twenty-three students completed the assignments. The course began with 25 students, thus it is unlikely that our data suffers from missing data, as noted in Becker and Power (2001).

4. HRSWORK is self-reported and thus may be subject to the "Lake Wobegon Effect" (Maxwell and Lopus, 1994). However, the typical USU student is a member of the LDS Church, which encourages its members to begin their married lives and careers earlier than the national average. We also compared self-reported GPA and CREDITS with official values from transcripts. Mean values for official and self-reported GPAs were 3.34 and 3.37, respectively, not statistically significantly different at the 95 percent level. The official and self-reported means for CREDITS were 14.25 and 12.05, respectively. This *under-reporting* of credit hours was significant at the 95 percent level.

5. This measure cannot account for the relative difficulty of questions and thus may overstate the loading behavior of some students (for those who backloaded their effort by having started the more difficult questions first).

6. We tested the standard model for heteroskedasticity and within-panel (AR1) autocor-

relation using feasible GLS (Greene, 2003). Results correcting for these possible error structures were qualitatively similar to those without the corrections, which are reported below. Alternative regressions were considered with a normalized score to control for difficulty across assignments, but results were again qualitatively similar. Panels are unbalanced due to a few missing values for the dependent variable, SCORE. Missing values occurred when students chose not to attempt some of the graded assignments.

7. For the standard model, the LM test rejects the pooled OLS model in favor of random effects, and the Hausman χ^2 test rejects FE in favor of RE. For the IV model, the Hausman χ^2 test similarly rejects FE in favor of RE.

8. Our results also suggest that, all else equal, students who completed practice assignments and had higher GPAs similarly performed better. Students who worked longer hours outside of school performed worse. The large coefficient for GPA could reflect the fact that the Aplia assignments are considered "advanced" by Bergstrom and Varian (2003). Or, GPA could be proxying for other unmeasured determinants of overall student capability.

9. To test whether procrastination has a negative effect on exam scores, we also ran a simple OLS regression of total exam points on GPA, GENDER, CREDITS, HRSWORK, and the averages of SKEW and START across the nine assignments. GPA had a strong positive effect, as did CREDITS. HRSWORK had a negative effect. However, averaged SKEW and START had no statistical effect. Thus, procrastination on homework assignments does not necessarily translate into poorer performance on exams.

10. In the case of front-/back-loaders, we find no evidence that an additional credit hour or an additional hour worked induces more back-loading. However, students did back-load their effort most during the middle of the semester. This could reflect conventional wisdom that students start the semester full of enthusiasm and finish in a state of

trauma, which reduces their penchant for backloading. Results are available from the authors.