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THE FOLLY OF DILLYDALLY

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Abstract

Using information from on-line graded assignments in an intermediate microeconomics course, we find that non-procrastinators (both early-starters and front-loaders) obtain higher scores than their dillydallying counterparts. We also find that while busier students tend to start their assignments earlier, they nevertheless back-load the bulk of their effort.

Keywords: Procrastination, early-/late-starters, front-/back-loaders, student performance

JEL: A14, A22, C23, I29

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1 Introduction

For advice to be sage it must be logical. It must also pass the test of time, i.e., be shown (at least anecdotally) to have been good advice across generations. And when available, empirical evidence must support it. Like most pieces of advice, "Stop dillydallying!", has passed the first two of these tests. It is for the most part logical, since procrastination generally does steal time. It has also been handed down to us by our parents ("clean your room now, not tomorrow"), our professors ("don't cram for the exam"), and is now passed by us to our students. However, because of our inability to

*We acknowledge the support of Lyssa Enzmann at Aplia for providing the data which has enabled the creation of our early-starter and front-loader variables and Sanjib Sarker for research assistance. We also thank the students who participated in this study.

actually measure the degree of procrastination among procrastinators, we have, until recently, been precluded from putting the advice to an empirical test.[1]

Thanks to web-based course-management systems such as WebCt and Blackboard, the ability to measure procrastination among college students has finally become a reality. This paper reports findings based on one such system, Aplia.[2] In Spring 2004, on-line practice and graded homework assignments were provided to students in an intermediate microeconomics course. Assignments for respective topics became available at the beginning of each week and were automatically graded at week's end. Students were able to access the assignments at any time during the week to answer any question in any order and to change answers whenever desired. Aplia recorded the dates and times that each question for each assignment was first accessed by the students.

By compiling this information, we are able to distinguish early- from late-starters and "front-loaders" from "back-loaders" (front-loaders access relatively more of their questions earlier in the week than back-loaders). We find that, all else equal, early starters and front-loaders score higher on their graded assignments. In other words, there is indeed folly in dillydallying. Further, we find evidence that busier students start assignments earlier than their less-occupied counterparts, but then back-load their effort.

The next section briefly describes the the Aplia assignments and our procrastination measures. Variable definitions and summary statistics for the panel data used in this study are also presented. Section 3 presents our empirical model and results. Section 4 concludes.

[1] The closest studies to ours are those by Borg et al. (1989), Johnson et al. (2002) and Krohn and O'Connor (2004), but these studies deal with measures of effort (often self-reported) rather than delay. Procrastination has nonetheless been the subject of an interesting strand of theoretical research (see Akerlof, 1991; O'Donoghue and Rabin, 1999 and 2001; and Fischer, 2001).

[2] Available at www.aplia.com.

2 Aplia and Measures of Procrastination

Students were required at the beginning of the semester to purchase online access to Aplia in order to obtain their weekly practice and graded homework assignments.[3] Practice assignments were optional, but highly recommended. Graded assignments were required. The assignments for each topic, beginning with budget constraints and ending with cost minimization, became available at the beginning of the week and were automatically graded at week's end.[4] There were a total of nine graded assignments throughout the semester. Students were able to access the problems at any time, in any order, and as many times as they desired prior to the grading deadline. Aplia kept track of the date and time that a student first accessed each problem from a graded assignment and then automatically graded each problem at the grading deadline. Students were subsequently provided with their scores and informational feedback on each question.

Definitions and summary statistics for the data used in this study are provided in Table 1. The first seven variables are based on information compiled by Aplia, while the remaining five were obtained via an end-of-semester survey. Of particular interest are the variables START and SKEW, which distinguish two different types of procrastinators. START measures the time difference (in days) between the grading deadline for a given graded assignment and when the student first accessed the assignment to answer a question. For example, if the grading deadline for the assignment was April 2nd at midnight, and the student first accessed the assignment on April 1st at 2 pm, the START value for this assignment would be 1.42 days. Students with relatively high (low) START values may therefore be considered early-

[3] A total of 22 students completed nine graded assignments, consisting of between four and eight questions per assignment.

[4] The textbook for the course was Varian (2003). The assignments, unbeknownst to the students, were taken directly from Bergstrom and Varian (2003). Because the assignments were posted en masse at the beginning of the semester, students had access to any graded assignment at any time before its due date. However, no students began an assignment before the beginning of the week that it was due.

(late-)starters. Late-starters are one type of procrastinator.

SKEW measures the skewness of the distribution of a student's time differences (in minutes) between the grading deadline and when the student first accessed each question contained in the assignment. This is a standard skewness measure, calculated as:

$$\frac{n}{(n-1)(n-2)} \sum_i \left(\frac{x_i - \bar{x}}{s} \right)$$

where n is the number of questions per assigment, x_i is the number of days prior to the due date that question i was started, $\bar{x}$ is the average number of days before the due date that questions were started, and s is the standard deviation. SKEW therefore accounts for 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) SKEW values are considered front-(back-)loaders. Back-loaders are a second type of procrastinator.

For example, suppose we have three students (1, 2, and 3) with respective START and SKEW values presented in Table 2. In this case, student 1 is an early-starting front-loader, student 2 is an early-starting back-loader, and student 3 is a late-starting front-loader.

3 Empirical Model and Results

We test our data for fixed and random effects using the standard panel-data model (Hsiao, 1986 and Greene, 2003):

$$y_{ij} = \mathbf{x'_{ij}}\boldsymbol{\beta} + v_{ij} \qquad i = 1, \ldots, n, \quad j = 1, \ldots, m \tag{1}$$

where y_{ij} is the SCORE for student i on assignment j; $\mathbf{x'_{ij}}$ is a vector of both assignment-variant and assignment-invariant explanatory variables taken from Table 1; and $\boldsymbol{\beta}$ is a corresponding coefficient vector. The expression for v_{ij} depends on whether pooled OLS, fixed, or random effects are assumed. In the case of pooled OLS, $v_{ij} = \alpha + \varepsilon_{ij}$, where α is a common intercept term across all students and assignments and ε_{ij} is an i.i.d. error

term with constant variance. For fixed effects (FE), $v_{ij} = \alpha_i + \varepsilon_{ij}$, where α_i is a student-specific intercept term (which therefore does not vary over assignments). For random effects (RE), $v_{ij} = \alpha + u_i + \varepsilon_{ij}$, where u_i is a student-specific random element, similar to ε_{ij}, except that for each student a single draw enters the regression identically for each assignment.

Results for the various specifications of (1) are presented in Table 3.[5] Based on the reported significance levels for the Breusch and Pagan (1980) LM and Hausman (1978) χ^2 specification tests, we focus our attention on the results for the FE model. We begin by noting that early-starters fair better than late-starters. For each day that a student first accesses an assignment before the grading deadline, their score increases by approximately 3.5 percentage points, all else equal. In addition, front-loaders add an average of approximately 11.35 percentage points to a given assignment. Procrastinators - both late-starters and back-loaders - therefore perform worse on graded assignments than their non-dillydallying counterparts.[6]

Recent theoretical contributions offer compelling interpretations of both rational (dynamically consistent) and irrational (dynamically inconsistent) procrastination. For example, Fischer (2001) models leisure as an exhaustible resource whose time-allocation with respect to work in any given period is (rationally) driven by the procrastinator's rate of time preference and elas-

[5]The results were obtained using Intercooled Stata 7.0 for Windows 95/98/NT. We have tested our model for heteroskedasticity, cross-sectional correlation, and within-panel (AR1) autocorrelation using feasible generalized least-squares (Greene, 2003). Our hypothesis for possible heteroskedasticity is that students with higher GPAs may exhibit a smaller error variance for SCORE. Within-panel autocorrelation could also exist due to the typical ebb and flow of the semester, i.e., students often report feeling "burned out" at some point near the middle to end of the semester. However, we have no a priori reason to expect cross-sectional correlation due to the inherent independence that exists between students. The results correcting for each of these possible error-structure complications were qualitatively the same as those obtained without the corrections. We therefore report the uncorrected results below

[6]Our results also suggest that students who completed the practice assignments performed better on the accompanying graded assignment, and that (based on results for the RE model) GPA has a similar positive effect on performance.

ticity of intertemporal substitution. To the contrary, Akerlof (1991) depicts procrastination as the (irrational) response to misperceived "salience costs" that inflate the total costs associated with current opportunities. As a result, the cost of procrastinating is reduced on tasks that can be completed in the future. O'Donoghue and Rabin (1999 and 2001) differentiate Akerlof's present-biased preferences between naïve and sophisticated procrastinators and introduce a menu of tasks on which the procrastinator might choose to procrastinate.

A common implication of these studies is that the relationship between the number of tasks facing the individual and the degree to which she will procrastinate on any given task is (positively) monotonic. For instance, Fischer's (2001) framework accommodates task aversiveness, whereby an optimizing student works on a less-aversive task first before moving on to a more difficult one. Task aversiveness therefore suggests that the more tasks required for the student to work on, the greater his chance of procrastinating longer on any given one. Indeed, O'Donoghue and Rabin (2001) show this result for a "partially" irrational procrastinator, which in turn supports Solomon and Rothblum's (1984) finding that the majority of procrastinators cite "too many other things to do" as a major reason for procrastinating.

We are able to test this "monotonic-procrastination" hypothesis for both late-starting and back-loading students. As Tables 4 and 5 demonstrate, the results across these two types of procrastinators are divergent with respect to the variable CREDITS. In the case of early-/late-starters (Table 4, with START as the dependent variable), enrolling for an additional credit hour induces an increase in start time by approximately 0.15 days. However, in the case of front-/back-loaders (Table 5, with SKEW as the dependent variable), an additional credit induces *more* back-loading.[7] Thus, students who presumably keep busier on campus dillydally less in terms of when they

[7]Since CREDITS is redundant in the model explaining SCORE (see Table 3), neither START nor SKEW are (statistically speaking) endogenous. The low R^2 for this model indicates that CREDITS nevertheless explains only a small amount of the total variation in SKEW.

start an assignment, but more in terms of when they choose to devote the bulk of their effort toward completing it. These divergent results suggest a refinement in our thinking about student procrastinators irrespective of whether their procrastination is a rational or irrational response to perceived opportunity costs.

4 Conclusions

Using information from on-line graded assignments, we find that non-procrastinators obtain higher scores than their dillydallying counterparts. This is true for both early-starters and front-loaders, although the magnitude of the front-loading effect on student performance is approximately three times larger than that of the early-starting effect. Taken together, these results suggest that the admonishment "Stop dillydallying!" is indeed sage advice.

We also find that while busier students tend to start their assignments earlier, they nevertheless back-load the bulk of their effort. These divergent results suggest an important tradeoff for university administrators concerned about student performance. Promotion of an accelerated graduation program (e.g., three- as opposed to four-year programs), which would apparently keep students busier over a shorter period of time, may induce more early-starting and back-loading behavior. Our results suggest that, given the relative magnitudes of these two types of procrastination, this type of program may in turn worsen student performance.

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Table 1: Variable Definitions and Summary Statistics

Variable	Description	Mean (SD)*
SCORE	Percentage correct per graded assignment.	69.89 (31.43)
PRACTICE	1 = attempted corresponding practice assignment, 0 = did not.	0.57 (0.50)
START	Time difference (in days) between the grading deadline for a given graded assignment and when the student first accessed the assignment to answer a question.	2.13(2.46)
STDEV	Standard deviation of the number of days before grading deadline that each problem was attempted per graded assignment.	0.26 (0.58)
SKEW	Skewness (in minutes).	0.23 (1.08)
SKEWDUM	1 = (Skew < 0), 0 otherwise.	0.35 (0.48)
INTACT	STDEV $\times$ SKEWDUM	0.10 (0.34)
GENDER	1 = male, 0 = female.	0.70 (0.46)
GPA	Grade point average (4.00 highest possible).	3.39 (0.35)
CREDITS	Total number of credits enrolled per student for semester.	11.78 (3.80)
HRSWORK	Total number of hours worked per week at a wage-paying job during semester.	18.27 (15.88)
CHILD	1 = has at least one child under the age of 18 living at home, 0 otherwise.	0.13 (0.34)

* Overall means (Mean) and associated standard deviations (SDs). The sample size for each of the variables is 207, except for GPA, CREDITS, and HRSWORK, which are 198 each.

Table 2: The Two Types of Procrastinators

Student	START	SKEW
1	3.5	-2.5
2	3.4	1.0
3	1.5	-0.5

Table 3: Effect of Procrastination on Score

Explanatory Variables	OLS	Fixed Effects (FE)	Random Effects (RE)
CONSTANT	-28.07	47.49**	-29.73
	(19.63)	(3.59)	(28.11)
PRACTICE	15.00**	17.47**	16.08**
	(3.96)	(4.79)	(4.24)
START	4.33**	3.51**	3.89**
	(1.00)	(1.00)	(0.98)
STDEV	5.11	6.44	5.84
	(5.99)	(5.73)	(5.68)
SKEWDUM	12.93**	11.35*	12.03**
	(4.71)	(4.56)	(4.50)
INTACT	-7.01	-11.60	-9.58
	(8.08)	(7.78)	(7.70)
GPA	21.32**		21.86**
	(5.72)		(8.22)
CREDITS	0.19		0.23
	(0.53)		(0.76)
$F(k, n-k)$	13.17**	10.77**	
Wald $\chi^2(k=7)$			74.05**
R^2	0.33	0.26	0.32
LM χ^2		12.96**	
Hausman χ^2		19.28**	

Standard errors are in parentheses. The number of observations is 198 for each regression model. ** Significant at the 1% level, * Significant at the 5% level.

Table 4: Determination of Late-Starting Procrastination

Explanatory Variables	OLS	Fixed Effects (FE)	Random Effects (RE)
CONSTANT	-1.19	1.66**	-1.37
	(1.75)	(0.29)	(2.31)
PRACTICE	0.42	0.85*	0.58
	(0.35)	(0.43)	(0.37)
GPA	0.44		0.46
	(0.49)		(0.66)
CREDITS	0.15**		0.16**
	(0.05)		(0.06)
HRSWORK	-0.01		-0.01
	(0.01)		(0.02)
CHILD	-0.44		-0.38
	(0.58)		(0.77)
$F(k, n-k)$	3.59**	3.97*	
Wald $\chi^2(k=7)$			11.69*
R^2	0.06	0.004	0.08
LM χ^2		1.94	
Hausman χ^2		1.70	

Standard errors are in parentheses. The number of observations is 198 for each regression model. ** Significant at the 1% level, * Significant at the 5% level.

Table 5: Determination of Back-Loading Procrastination

Explanatory Variables	OLS	Fixed Effects (FE)	Random Effects (RE)
CONSTANT	0.72	0.26*	0.72
	(0.80)	(0.14)	(0.84)
PRACTICE	-0.04	-0.08	-0.04
	(0.16)	(0.20)	(0.16)
GPA	-0.34		-0.34
	(0.23)		(0.24)
CREDITS	0.05*		0.05*
	(0.02)		(0.02)
HRSWORK	0.005		0.005
	(0.006)		(0.006)
CHILD	-0.18		-0.18
	(0.27)		(0.28)
$F(k, n-k)$	1.79	0.17	
Wald $\chi^2(k=7)$		8.16	
R^2	0.02	0.0003	0.04
LM χ^2		0.36	
Hausman χ^2		0.10	

Standard errors are in parentheses. The number of observations is 198 for each regression model. ** Significant at the 1% level, * Significant at the 5% level.