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Estimating the effects of procrastination on performance: A small sample study☆

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ABSTRACT

Previous studies have found student procrastination to compromise learning outcomes using initial test scores to control for the influence of unobserved ability. The validity of such analysis rests on the assumption that students do not react to initial test scores. Utilizing daily information on student behavior, this paper shows that feedback effects were negligible in a student sample from a university second-language course. The paper then objectively quantifies the degree of procrastination, and finds evidence for detrimental effects of procrastination on test scores, corroborating previous studies. The result lends confidence to the value-added specification of the education production function.

1. Introduction

Recent economics studies examine whether student procrastination affects test performances using observational data (Wong, 2008; Donovan et al., 2006).[1] Procrastination, meaning acts or habits of putting things off, has drawn attention of economists out of interests on the self-control problems of decision makers. Thaler and Sunstein (2003) among others advocate paternalistic interventions in wide aspects of the economy to redress suboptimal outcomes arising from time-inconsistent preference. While Wong (2008) and Donovan et al. (2006) have found detrimental effects of procrastination in classes, a question on causality remains: Do their non-experimental results suffer from an endogeneity bias arising from correlations between the degree of procrastination and unobserved ability?

A common solution to remove potential biases arising from any correlation between ability and study patterns is to adopt the value-added specification of an education production function that includes test scores at the beginning of sample period (hereafter "pretest") as a proxy for unobserved ability. In using pretest to control unobserved ability, however, researchers make an implicit assumption regarding the effects of a student's pretest performance on his/her subsequent study behavior. If a student performs better on the pre-test than he should have done (e.g. he guesses more correct answers than would be expected by chance on questions that he does not know the correct answer to), he may become overconfident and choose to slack on the homework. Similarly, students whose performance is lower than their true ability may attempt to compensate by expending more effort throughout the remainder of the course to make up for their lower-than-expected baseline ability. This dynamic will induce a positive correlation between effort and test score improvement even if effort has no effect on learning. A number of empirical studies document the existence of 'feedback effects' (Azmat and Iriberri, 2010; Bandiera et al., 2008; De Paola and Scoppa, 2010). In settings where we suspect feedback effects exist, the value-added specification of an education production function may produce biased estimates.

This paper has two aims: first is to outline the conditions under which the effects of procrastination are identified in a non-experimental study. As will be analytically shown, an endogenous input in an education production function is correlated with error term if feedback effects exist. The second aim is to examine any potential bias arising from feedback effects utilizing a very small but highly detailed dataset on student behavior.

My observational data is drawn from a setting where students' activities on assignments are recorded through online software. This allows me to quantify the degree of procrastination based on objectively collected data. Further, I obtained rich information on

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[1] Donovan et al. (2006) estimate a value-added specification on a sample of US college students. Wong (2008) estimates a contemporaneous specification on a sample from a Singaporean University.

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concurrent study inputs and background characteristics through survey. A drawback to this rich individual-level data is the sample size, which is nonetheless comparable to those from small-scale clinical trials. Estimates of an education production function show a negative and significant correlation between procrastination on performance. An auxiliary examination estimates a two-way fixed effects model to gauge the effects of weekly quizzes on study time, and found feedback effects to be negligible. Thus, procrastination does seem to reduce performance in my sample of students.

The contributions of this paper are twofold. First is additional non-experimental evidence on procrastination and performance, lending confidence to results from Wong (2008) and Donovan et al. (2006). Unlike these previous studies, current paper outlines explicitly the identifying assumptions, and conducts an auxiliary test to validate the assumption on no feedback effects. Second, more broadly, is evidence on the reliability of a value-added specification of education production functions. As clearly articulated by Todd and Wolpin (2003), a number of assumptions are required in consistently estimating education production functions. Applied analyses often implicitly take them as given. This study presents a case in which the concern about the feedback effects is not significant for a semester-length course.

In the reminder, Section 2 discusses the model. Section 3 presents results. Section 4 examines feedback effects. Section 5 concludes.

2. Education production function

Todd and Wolpin (2003) consider an education production function in the context of a child's entire life; their conceptual framework incorporates the initial endowment of ability as well as the current and past inputs provided by parents and schools. The settings for procrastination studies are semester-length classes where relevant inputs are student efforts and other sources of learning. A body of related studies investigates the effects of, for example, lecture attendance (Romer, 1993). My model extends Todd and Wolpin (2003) by explicitly writing out structural equations to obtain a recursive system (Krohn and O'Connor, 2005).

$$T_i^0 = X_i'\beta^0 + \mu_i^0 + \varepsilon_i^0 \tag{1.1}$$

$$E_i = X_i'\beta^1 + T_i^0\delta + \mu_i^1 + u_i + \varepsilon_i^1 \tag{1.2}$$

$$T_i^2 = X_i'\beta^2 + E_i\theta + \mu_i^2 + \varepsilon_i^2 \tag{1.3}$$

T_i^0 and T_i^2 are test scores from pretest and posttest respectively. E_i is a variable summarizing at the semester level learning activities conducted by student i (hereafter "effort"). Test scores, as well as effort levels, depends on common factors, X_i is a vector of exogenous individual characteristics. μ_i^j is an unobservable ability. Superscripts on β^j and μ_i^j indicate that effects vary across equations. μ_i^j is correlated across equations. u_i is an unobservable motivation possibly correlated with ability. This specification assumes motivation affects learning indirectly through efforts. ε_i^j is stochastic disturbance uncorrelated with one another and with the exogenous regressors.

A least square regression on the posttest equation (1.3) is biased if the unobservable ability affects outcomes. The direction of the bias is upward if able students exert greater efforts. Subtracting γT^0 from T^2 yields a general specification of a value-added specification.

$$T_i^2 = X_i'(\beta^2 - \gamma\beta^0) + E_i\theta + \gamma T_i^0 + (\mu_i^2 - \gamma\mu_i^0) + (\varepsilon_i^2 - \gamma\varepsilon_i^0) \tag{2}$$

Consider a special case where $\mu_i^0 = \phi_0\mu_i$ and $\mu_i^2 = \phi_2\mu_i$ (Dolton et al., 2003), where μ_i is a time-invariant ability. Since $\gamma = \phi_2/\phi_0$, the direct effects of unobserved abilities are removed from (2); T_i^0 thus serves as a proxy for the ability in this special case.

Although the inclusion of pretest score removes unobserved ability in this special case, the estimate of θ can still be biased from the feedback effects: if a negative shock at the pretest led to more (or less) efforts, E_i is correlated with the component of a disturbance term, ε^0. Notice, however, that a disturbance term captures a deviation of test scores from his/her "true" potential. For example a student might have had a bad test day due to stomach ache. If a student is aware that he/she has had a bad test day, he/she may correctly infer that his/her poorer than expected performance was simply unlucky and would not react to the experience by exerting more effort that he/she would have done without the stomach ache. Any feedback effects, even if they exist, should be sufficiently small to induce a large bias in this case.

Should we then expect the assumption $\delta = 0$ to hold a priori? In a context where a student know his/her potential in absolute term but not in relative term, $\delta = 0$ is a strong assumption since pretest scores would provide students with information on their relative standing in a group and thus induce students to react. Indeed, Azmat and Iriberri (2010) document information on relative standing affects behavior. Assessment grades are often "curved" so that relative standing is of importance to students. Thus, an assumption, $\delta = 0$, is also necessary even in this special case.

T^0 is in addition mechanically correlated with the residual (ε^0) but the consensus in the dynamic panel regression literature is that coefficients on lagged dependent variables are biased more severely than coefficients on covariates (Judson and Owen, 1999); indeed this source of bias seems negligible in my application. In summary, the key assumptions required to obtain consistent estimates are: (1) $\mu_i^j = \phi_j\mu_i$ for $j = 0, 2$ and (2) $\delta = 0$.

3. The effects of procrastination in a language course

In the class sample drawn from a university in Japan, an instructor required students to complete 60 drills on English-listening activities in software called ALCNA by a deadline set at the 17th week from the beginning of the semester. This assignment weighs 30% of the course grade. The software records the amount of time students spent on different parts within a drill that would take an average student about 10–15 min to complete. This course aimed to develop student's listening English skills and tested students with exams, conducted before and after the course, using a test format similar to a standardized language qualification exam. A survey was conducted to obtain background characteristics and attitudinal measure on the interests English and motivation for learning the language. The instructor has provided me with the record of attendance (a part of assessment) and the results of weekly quizzes. The sample used in analysis consists of 62 students.

The empirical analysis aims to obtain a consistent estimate of the effects of procrastination on test performance. The following model is estimated using OLS.

$$T_i^2 = X_i'\varphi + E_i'\theta + \gamma T_i^0 + \upsilon_i \tag{3}$$

X_i is a vector of covariates, including gender, senior students, private high school attendance, class preference, experience living abroad, home prefecture, membership of a university sport clubs, part-time works, and 6 survey items intended to measure the motivations for learning English, such as the strength of interests on a study abroad programs, and attitude toward computer-assisted learning. E_i includes five measures of study inputs. First is the degree of procrastination measured with the