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Can Investments in Education be Incentivized?: The Impact of Performance-Based Scholarships on Student Time Use

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The Impact of Performance-Based Scholarships on Student Time Use

Abstract

There has been increased interest in using incentives to improve educational outcomes by providing students with a bigger, more immediate, pay-off to working hard in school. While a growing literature evaluates the impact of these strategies on student educational outcomes, results have been mixed raising the question of whether such incentives actually change student effort towards their educational attainment. We evaluate the effect of two post-secondary incentive scholarship programs on a variety of outcomes, in particular, their effect on investments in education as reflected in how students spend their time. In these randomized experiments, incentive payments that varied in magnitude and number of semesters of eligibility were tied to meeting enrollment, attendance and/or performance benchmarks.

We find that students eligible for a performance-based scholarship devoted more of their time to educational activities, especially test preparation, devoted less time to leisure activities, and increased the quality of effort toward, and engagement with, their studies as measured by indices of learning strategies and academic self-efficacy. Further, results suggest that students were motivated more by the incentives provided by the scholarships rather than simply the income effect of giving them more money. Finally, students who were plausibly less time-constrained were generally more responsive to the incentives as were those who were plausibly more myopic. While no single test was dispositive, overall we find consistent evidence that students can, and do, respond to such incentives.

I. Introduction

Educators have long been worried about relatively low levels of educational performance among U.S. students.[1] At the elementary and secondary school levels, students in the U.S. perform relatively poorly on academic tests compared to their peers in comparable countries (Baldi et al., 2007). At the post-secondary level there is increasing concern that while the U.S. has one of the highest rates of college attendance in the world, rates of college completion lag those of other countries (*OECD Indicators,* 2011). In response, educators have proposed and implemented many policies aimed at changing the curriculum, class size, teacher effectiveness, and other resources at all levels of schooling. More recently, there has been interest in targeting another key component: the effort exerted by students themselves towards their studies.

One approach to motivating students to work harder in school has been to offer them rewards for achieving prescribed benchmarks. Related to the conditional cash transfer strategies that have been growing in popularity in developing countries (see, e.g., Das et al., 2005 and Rawlings and Rubio, 2005), U.S. educators have implemented programs in which students are paid for achieving benchmarks such as a minimum grade-point average (GPA) or for reading a minimum number of books. These strategies are based on the belief that current pay-offs to education are too far in the future (and potentially too "diffuse") to motivate students to work hard in school. As such, by implementing more immediate pay-offs, these incentive-based strategies are designed to provide students with a bigger incentive to work hard.

Unfortunately the evidence to date of such efforts has yielded somewhat mixed, and often small, impacts on student achievement, especially at the post-secondary level. For example, Jackson (2010a,b) finds some evidence that the Advanced Placement Incentive Program (APIP)

[1] For example, the 1983 report on American education, "A Nation at Risk" spurred the most recent wave of concern regarding poor academic performance at nearly every level among U.S. students.

in Texas—which rewards students (and teachers) for AP courses and exam scores—increased scores on the SAT and ACT Tests, increased rates of college matriculation and persistence, and improved post-secondary school grades. These results are similar to those reported by Angrist and Lavy (2009) from a high school incentive program in Israel. Somewhat in contrast, Fryer (2012) reports suggestive evidence that rewarding elementary and secondary school students for effort focused on education inputs, such as reading books, may increase test score achievement while rewarding them for education outcomes, such as grades and test scores, does not. At the post-secondary level, estimated impacts have been more modest. For example, Angrist, Lang, and Oreopoulos (2009) and Angrist, Oreopoulos, and Williams (2012) report small impacts at a 4-year college in Canada, although impacts may be larger for some subgroups.[2] Barrow, et al. (2012) report positive impacts on enrollment and credits earned for a program aimed at low-income adults attending community college in the U.S., and early results from MDRC's Performance-based Scholarship Demonstration (described below) suggest modest impacts on some academic outcomes (such as enrollment and credits earned) but little impact on persistence (see Richburg-Hayes et al., 2011; Cha and Patel, 2010; and Miller et al., 2011).

The fact that impacts of incentives on academic outcomes have been small, at best, raises the question of whether educational investments can be effectively incentivized in the sense that they actually change student behavior. Alternatively it is also possible that these small positive results arise from statistical anomaly or represent changes along other dimensions such as by taking easier classes. In this paper, we evaluate the effect of two performance-based scholarship programs for post-secondary students on a variety of outcomes, but especially on student effort as reflected in time use. Students were randomly assigned to treatment and control groups where

[2] Specifically, Angrist, Lang, and Oreopoulos (2009) report larger impacts for women, although the subgroup result is not replicated in Angrist, Oreopoulos, and Williams (2012). Angrist, Oreopoulos, and Williams (2012) report larger effects among those aware of the program rules.

the treatments (the incentive payments) varied in length and magnitude and were tied to meeting enrollment, attendance, and/or performance benchmarks. To better understand the impact of performance-based scholarships on student educational effort, we implemented a time diary survey for which we used the *American Time Use Survey* (ATUS) as a template. Further, working from the incentive structure of the scholarships, we also examine whether the program had larger impacts for those students with greater ability to shift their time use and those hypothesized to be more "myopic."

We find evidence that students eligible for a performance-based scholarship devoted more of their time to educational activities, especially test preparation, devoted less time to leisure activities, and increased the quality of effort toward, and engagement with, their studies as measured by indices of learning strategies and academic self-efficacy. The results also suggest that students were motivated more by the incentives provided by the scholarships rather than simply the income effect of giving them more money. Finally, students who are plausibly less time-constrained are more response to the performance-based scholarships as those who are plausibly more myopic. While no single test is dispositive, taken together these results suggest that most post-secondary students can, and do, increase investments in educational attainment with well-designed incentives.

We next discuss a theoretical framework for thinking about effort devoted to schooling and the role of incentive scholarships followed by a description of the two interventions we study in Section III. In Section IV, we describe the data and present sample characteristics of program participants. The estimation strategy and results are presented in Section V, and Section VI concludes.

II. Theoretical framework

A. Academic Effort

Following the model outlined by Becker (1967), economists typically hypothesize that students continue their education until the marginal cost outweighs the marginal benefit. Suppose that student i's GPA depends on ability a_i, effort e_i, and some random noise ε_i as follows:

$$g_i = e_i + a_i + \varepsilon_i \quad . \tag{1}$$

Let ε be distributed, $F(\varepsilon)$, with density $f(\varepsilon)$, and let $c(e)$ reflect the cost of effort. Assume $c'(e) > 0$ and $c''(e) > 0$. Further assume there is a payoff W for achieving a minimum GPA g^{min} with a payoff of zero otherwise.[3] Assuming students maximize utility by maximizing the net expected benefit of effort, the student's maximization problem is as follows:

$$\text{Max}_e\{[1 - F(g^{min} - e_i - a_i)] \cdot W - c(e_i)\} \text{ s.t. } e_i \geq 0 \ . \tag{2}$$

Assuming the second order conditions are satisfied, the optimal value of effort, e_i^*, is characterized by the first-order condition:

$$c'(e_i^*) \geq f(g^{min} - e_i^* - a_i) \cdot W \ . \tag{3}$$

Thus, a student may not enroll or continue in college because the marginal benefit is relatively low and/or because the marginal costs are relatively high. The research evidence on whether the benefit of each additional year (or credit) is lower for dropouts than for students who stay in school is inconclusive (Barrow and Rouse, 2006), but there are many reasons to think that the costs, broadly construed, may differ across students. For example, those individuals with more family responsibilities (such as parents, especially those with young children) may find it quite costly to put more effort, in terms of time, into their studies. Similarly, those for whom academic endeavors require more psychic energy, such as those not well prepared for college-

[3] Alternatively, one could think about there being a payoff to each course completed with a minimum grade level. We abstract from the possibility of a higher payoff to achieving grades above the minimum threshold.

level work, may find the cost of reaching the stipulated benchmark(s) quite high and therefore would not be as responsive to the incentive.

B. Policy Intervention and Performance-based Scholarships

Traditional need-based and merit-based scholarships provide an incentive to enroll in college by effectively lowering the costs of enrolling in college regardless of whether the student passes her classes once she gets there. In the theoretical model above, these types of scholarships have no impact on the marginal value or cost of effort conditional on enrolling in school, except for the case in which future scholarship receipt depends on meeting the g^{min} benchmark in the current semester. Performance-based (PB) scholarships are hypothesized to improve student outcomes by increasing the immediate financial benefits from effort towards schoolwork in the current semester. For example, payments may be contingent on meeting benchmark performance goals such as a minimum GPA. Because a PB scholarship increases the immediate financial rewards to effort, we would expect PBS-eligible students to allocate more time to educationally productive activities, such as studying, which should in turn translate into greater educational attainment, on average.

However, there may also be some heterogeneity in responsiveness across students. If the density f() in equation (3) is roughly normally distributed with small values in the tails, then whether and by how much a performance incentive changes an individual student's effort will depend on ability/preparation and the marginal cost of effort. For a high-ability student, increasing the payoff W will have little effect on her effort because she will essentially be able to meet the minimum GPA requirement on ability with no increased effort because her prior ability/preparation alone put her in the right tail of the density. Similarly, low ability (or very

poor preparation) will put a student in the left tail of the distribution and an increase in *W* will have little effect on her effort because the probability of meeting the minimum GPA requirement, even with high levels of effort, is so low and effort is costly. For students in the middle range of ability/preparation, the performance incentive will cause them to increase effort in order to increase the probability of meeting the minimum GPA requirement. We also expect that the performance incentive will have bigger impacts on effort for students who are more "myopic" (those who heavily discount future benefits) as the returns to schooling in terms of future earnings should already motivate less-myopic students but may be too far in the future to have an impact on more present-oriented students. On the cost side (all else equal) we would expect to see students facing a higher marginal cost of effort (such as those with small children) to have a smaller change in effort in response to changes in the payoff *W* than students facing a lower marginal cost of effort.

While the intention of a performance-based scholarship is to increase student effort in educationally productive ways, there may be unintended consequences as well. Indeed, Cornwell, Lee, and Mustard (2005) find that the Georgia HOPE scholarship which had grade incentives but not credit incentives reduced the likelihood that students registered for a full credit load and increased the likelihood that students withdrew from courses presumably to increase the probability that they met the minimum GPA benchmark. Other unintended consequences could be cheating on exams, asking professors to regrade tests and/or papers, or taking easier classes.

Further, psychologists worry that while such incentives may motivate students to do better in the short term, they may be motivated for the wrong reasons. Psychologists distinguish between internal (or "intrinsic") motivation in which a student is motivated to work hard because he or she finds it inherently enjoyable or interesting and external (or "extrinsic") motivation in

which a student is motivated because it leads to a separable outcome (such as a performance-based scholarship) (see, e.g., Deci (1975) and Deci and Ryan (1985)). A literature in psychology documents more positive educational outcomes the greater the level of "internalization" of the motivation (e.g., Pintrich and De Groot, 1990). As such, one concern among opponents of performance-based rewards in education is that such scholarships may increase external motivation and may even decrease internal motivation (e.g., Deci, Koestner, and Ryan, 1999).

III. The Scholarship Programs and the Time-Use Survey

The data we analyze were collected as part of the Performance-Based Scholarship (PBS) Demonstration conducted by MDRC at 8 institutions and at a state-level intermediary in California. The structure of the scholarship programs as well as the populations being studied vary across the sites; this study presents results from a supplementary "Time Use" module we implemented at sites in New York City (NYC) and California (CA).[4] In both demonstrations we analyze, the scholarships supplemented any other financial aid for which the students qualified (such as federal Pell Grants and state aid) although, in theory, institutions could have adjusted aid awards in response to scholarship eligibility.

A. The Scholarship Programs

<u>The New York City Program</u>

The intervention in New York City was implemented at two campuses of the City University of New York System (CUNY) – the Borough of Manhattan Community College (BMCC) and Hostos. Students were recruited on campus in three cohorts (Fall of 2008, Spring

[4] See Richburg-Hayes (2009) for more details on the programs in each site in the larger demonstration.

2009, and Fall 2009). Eligible students were aged 22-35, required to take at least one developmental course, eligible for a federal Pell Grant, enrolled in at least 6 credit or contact hours (at the time of "intake"), and lived away from their parents. Once program staff determined eligibility for the study, students who agreed to participate provided baseline demographic information and were randomly assigned by MDRC to the program or control groups. Everyone who attended an orientation session (at which they were introduced to the study) and signed up to participate in the study received a $25 metro card.

Students randomly assigned to a program (treatment) group were eligible to receive a performance-based scholarship worth up to $1,300 each semester for two semesters (for a total of $2,600).[5] As the goal of this scholarship was to reward attendance (an input to academic success) as well as performance at the end of the semester, the incentive was structured as follows for the scholarships: After registration (meaning tuition had been paid or a payment plan had been established) the student received $200; with "continued enrollment at mid-semester" he or she received $450; and with a final grade of "C" or better (or passed developmental education) in at least 6 credits (or equated credits), he or she received $650.[6] So as not to discourage students mid-semester, if a student missed the mid-semester payment it could be recouped at the end of the semester if the final requirement was met. The entire incentive could be repeated a second semester independent of having met any of the first semester benchmarks.[7]

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[5] In reality in NYC some students were randomly assigned to a second treatment group that was eligible to receive the performance-based scholarship during the regular semesters plus a performance-based scholarship for one consecutive summer worth up to $1,300 (for a total of $3,900). Because we focus on regular semester outcomes during which the incentive structures for the two treatment groups are identical, we do not present results separately for the two treatment groups in this paper. Results in Appendix Table 3 suggest impacts were similar for the two treatments.

[6] "Continued enrollment at mid-semester" was determined by whether the student attended at least once in the first weeks of the semester and at least once during the fourth or fifth weeks of the semester. Equated credits are given in developmental education classes and do not count towards a degree or certificate.

[7] See Richburg-Hayes, Sommo, and Welbeck (2011) for more background on the New York demonstration.

The California Program

The California program is unique in the PBS demonstration in that random assignment took place in the spring of the participants' senior year of high school and students could use the scholarship at any accredited institution.[8] All participants had attended a "Cash for College" workshop at which attendees were given assistance in completing the Free Application for Federal Student Aid (FAFSA) and had completed the FAFSA by April 1 of the year in question. Participating students were selected from sites in the Los Angeles and Far North regions in 2009 and 2010 and from the Kern County and Capitol regions in 2010. Randomization occurred within each workshop in each year. Because the students were high school seniors at the time of random assignment, this demonstration allows us to determine the impact of these scholarships not only on persistence among college students, but also on initial college enrollment.

To be eligible for this study, participants had to have attended a Cash for College workshop in one of the participating regions; been a high school senior at the time of the workshop; submitted a Free Application for Federal Student Aid (FAFSA) and Cal Grant GPA Verification Form by the Cal Grant deadline (early March); met the low-income eligibility standards based on the Cal Grant income thresholds; and signed an informed consent form or had a parent provide consent for participation.

The incentive varied in length (as short as one semester and as long as four semesters), size of scholarship (as little as $1000 and as much as $4000), and whether there was a performance requirement attached to it. Specifically Table 1, below, shows the structure of the demonstration for the Fall 2009 cohort; it was similar for the Fall 2010 cohort. There were six

[8] At the other sites, the scholarships were tied to enrollment at the institution at which the student was initially randomly assigned. In addition, all of the other study participants were at least "on campus" to learn about the demonstration suggesting a certain degree of interest in and commitment to attending college. See Ware and Patel (2012) for more background on the California program.

treatment groups labeled 1 to 6 in Table 1. Group 1 was randomly selected to receive a California Cash for College scholarship worth $1,000 which is a typical grant that has no performance component and is paid directly to the student's institution. Groups 2 through 6 had a performance-based component. Group 2 was randomly assigned to receive $1,000 over one academic term (a semester or quarter); group 3 was randomly selected to receive $500 per semester for two semesters (or $333 per quarter over three quarters); group 4 was selected to receive $1,000 per semester for two semesters (or $667 per quarter over three quarters); group 5 was to receive $500 per semester for four semesters (or $333 per quarter over six quarters); and group 6 was to receive $1000 per semester for four semesters (or $333 per quarter over six quarters). During fall semesters of eligibility, one-half of the PB scholarship was paid conditional on enrolling for six or more credits at an accredited, degree-granting institution in the U.S., and one-half was paid if the student met the end-of-semester benchmark (a final average grade of "C" or better in at least 6 credits). During spring semesters of eligibility, the entire scholarship payment was based on meeting the end-of-semester benchmark.

Table 1: Structure of the California Program

Scholarship Type	Total Amount	Performance Based?	Duration	Fall 2009		Spring 2010	Fall 2010		Spring 2011
				Initial	Final		Initial	Final	
1	$1,000	No	1 term	$1,000					
2	$1,000	Yes	1 term	$500	$500				
3	$1,000	Yes	1 year	$250	$250	$500			
4	$2,000	Yes	1 year	$500	$500	$1,000			
5	$2,000	Yes	2 years	$250	$250	$500	$250	$250	$500
6	$4,000	Yes	2 years	$500	$500	$1,000	$500	$500	$1,000

Source: Ware and Patel (2012). The dates refer to the incentive payouts for the 2009 cohort but the structure is the same for the 2010 cohort. The schedule shown applies to institutions organized around semesters; for institutions organized into quarters the scholarship amount is the same in total but the payments are divided into three quarters in the academic year.

In addition, aside from the institution being accredited, there were no restrictions on *where* the participants enrolled in college. That said, according to data from the Cash for College workshops, among the two-thirds of students who enroll in college the following fall over 90% attend a public college or university within California, about one-half in a two-year college and the other half in a four-year institution.

B. Numbers of Participants

In Table 2 we present information on the number of students in each cohort in each demonstration. In total 6,662 individuals were recruited to be part of the PBS study; 2,474 were randomly assigned to the program-eligible group and 4,188 were assigned to the control group.[9] Our California sample includes an additional 1,500 individuals in the control group who were randomly selected from non-study group individuals who were not selected to be in either the program or control group. Appendix Tables 1a and 1b show means of background characteristics (at baseline) by treatment/control status. While there are one or two characteristics that appear to differ between treatment and control groups, an omnibus f-test yielded a p-value of 0.68 in Appendix Table 1a for NYC and 0.55 in Appendix Table 1b for CA suggesting that randomization successfully balanced the two groups, on average.

According to Richburg-Hayes and Patel (forthcoming) nearly all (99%) of the treatment students in NYC received the initial payment the first semester and 97% received the midterm payment (that required continued enrollment, as defined above); 72% received the performance-based payment at the end of the term. Scholarship receipt was lower in the second semester with

[9] We did not receive contact information for one individual in New York so the total number of individuals we attempted to survey in New York and California combined is 8,161.

only 83% receiving the first payment, 80% receiving the second, and 58% receiving the final payment. In CA, initial results for cohort 1 reported in Ware and Patel (2012) indicate that 85 percent of the scholarship eligible participants received an enrollment payment and of those, 60 percent earned the performance-based payment at the end of the fall 2009 semester.

C. Time Use Survey[10]

To better understand the impact of performance-based scholarships on student educational effort, we implemented an independent survey of participants. While we asked respondents general questions about educational attainment and work (roughly based on the *Current Population Survey*), the centerpiece was a time diary for which we used the *American Time Use Survey* (ATUS) as a template. Accounting for an entire 24-hour time period, the ATUS asks the respondent to list his or her activities, describe where the activities took place, and with whom. In designing our survey we started with the basic structure of the ATUS in the core of the survey, but also included questions about time use over the last 7 days to accommodate those activities that are particularly relevant to students and for which it would be valuable to measure over longer periods (such as time spent studying per day over the past week). Participants were offered an incentive to participate.

In addition to the questions regarding time use over the previous 24 hours or 7 days, the survey also included questions to measure learning strategies, academic self-efficacy, and motivation. We included questions on learning strategies and self-efficacy to capture increases in the quality of educational effort as distinct from the quantity (in terms of time). Further, researchers have documented a link between perceived self-efficacy (e.g., an individual's

[10] We only briefly describe the survey in this section. See Barrow and Rouse (in progress) for more details on the survey design and implementation.

expectations regarding success or assessment of his or her ability to master material) and academic performance (see, e.g., Pintrich and De Groot 1990). To capture these other forms of "effort," the survey also included questions from the Motivated Strategies for Learning Questionnaire (MSLQ) that are designed to capture learning strategies that should help students perform better in class (Pintrich et al. 1991). The scale consists of five questions on a seven-point scale with questions such as: "When I become confused about something I'm reading, I go back and try to figure it out" (responses range from not at all true (1) to very true (7)). In addition, we included five questions that form a scale to capture perceived academic efficacy (the *Patterns of Adaptive Learning Scales* (PALS) by Midgley et al. 2000). These questions are of the form: "I'm certain I can master the skills taught in this class this year" with responses on a similar seven-point scale.

Finally, we attempted to assess whether the incentives also induced unintended consequences such as cheating, taking easier classes, or attending classes simply to receive the reward not because of an inherent interest in the academics (which some psychologists argue can ultimately adversely affect academic achievement, as discussed earlier). As such, on the survey we asked participants about life satisfaction, whether they had taken "challenging classes," if they had ever asked for a regrade, and if they had ever felt it necessary to cheat. To capture external and internal motivation, we asked questions of both current students and those not currently enrolled along the lines of, "If I do my class assignments, it's because I would feel guilty if I did not" (also on a seven-point scale).[11]

[11] Specifically, "external motivation" is the mean of two questions: "If I attend class regularly it's because I want to get a good grade" and "If I raise my hand in class it's because I want to receive a good participation grade." "Internal motivation" is the mean two questions: "If I turn in a class assignment on time it's because it makes me happy to be on time" and "If I attend class often it's because I enjoy learning."

We focus this analysis on time-use and effort in the first semester after random assignment as the majority of both program and control students were enrolled in a post-secondary institution such that an analysis of time use is most compelling as one of the factors that determine educational success.[12] That said, we also surveyed each cohort in the second semester after random assignment to gauge the extent to which time use changed and whether differences between the program and control group members persisted. Overall we achieved an average response rate of about 73% in New York City and about 57% in California in terms of the percentage of participants that ever responded to a survey.

Table 3 presents selected mean baseline characteristics for study participants at the time of random assignment and compares them to nationally-representative samples of students from the *National Postsecondary Student Aid Study (NPSAS) of 2008* designed to be comparable to the participants in the study.[13] In both sites there were slightly more women than men. Further, the proportion of hispanics and blacks was much higher in the study sites than nationally. For example, in NYC 80% of the participants were black or hispanic compared to 40% nationally and in CA 60% of participants were hispanic, compared to 20% nationally, and there were no blacks. Similarly, in both sites a language other than English is likely to be spoken. That said, aside from the racial/ethnic composition, the baseline characteristics of the study participants resemble those of other post-secondary students nationally.

IV. Estimation and Results

A. Empirical Specification and Sample

[12] Because we focus on the first semester after random assignment, we do not include data from the first cohort in New York City as we were only able to first survey them in the second semester after random assignment.

[13] The baseline data were collected by MDRC at the time participants were enrolled in the study and before they were randomly assigned to a program, control, or non-study group. The samples from the NPSAS have the same age ranges as the two sites. See the notes to the tables for other sample restrictions.

Below we present estimates of the effect of program eligibility on a variety of outcomes. We model each outcome Y for individual i as follows:

$$Y_i = \alpha + \beta T_i + X_i\Theta + p_i\gamma + v_i\,, \tag{4}$$

where T_i is a treatment status indicator for individual i being eligible for a program scholarship, X_i is a vector of baseline characteristics (which may or may not be included), p_i is a vector of indicators for the student's randomization pool, v_i is the error term, and α, β, Θ, and γ are parameters to be estimated; β represents the average effect on outcome Y of being randomly assigned to be eligible for the scholarship. In some specifications, we allow for a vector of treatment indicators depending on the type of scholarship for which the individual was eligible.

From our data, we focus on respondents to the first survey administered in the first semester after random assignment. After dropping individuals who did not complete the time diary (or who had more than four "non-categorized" hours in the 24-hour time period) and those for whom we did not have data in the first part of the survey (due to an error by the survey contractor), we have data from 2,874 complete surveys in CA and 613 surveys in NYC. These complete surveys represent 92% and 93% (respectively) of the total number of survey respondents. Appendix Tables 2a and 2b show means of background characteristics (at baseline) by treatment/control status for our analysis sample. Again, while there are one or two characteristics that appear to differ between treatment and control groups, omnibus f-tests suggest that the two groups remain balanced, on average.

B. Basic Program Impacts on Educational and Other Outcomes

In Table 4 we present estimates of the effect of program eligibility on educational outcomes as measured by the time use survey; in this table we do not distinguish between the

types of performance-based scholarships offered in the two sites. In column (1) we provide outcome means for the control group participants in New York City, and in column (4) we provide outcome means for the control group participants in California. Program effect estimates with standard errors in parentheses are presented in column (2) for New York and columns (5) and (6) for California. Note that the estimates in column (5) reflect the impact of being eligible for a PB scholarship while the estimates in column (6) reflect the impact of being eligible for a non-PB scholarship. The p-value corresponding to the test that the PBS program impact equals the non-PBS program impact is presented in column (7). Program effects are estimated including controls for randomization pool fixed effects but no other baseline characteristics.[14]

In New York City we find that program-eligible students are no more likely to report ever enrolling in a post-secondary institution since random assignment than those in the control group. This result is not particularly surprising given that students were on campus when they were recruited for the program. As evidence, 92% of NYC control-group students report ever attending a post-secondary institution since random assignment. In contrast there are larger differences in variables reflecting student effort. For example, 78% of control group students report having attended most or all of their classes in the last seven days compared to 84% of students eligible for a performance-based scholarship, a difference that is statistically significant at the 10 percent level. Control group students report spending about 2.8 hours per day studying in the last seven days, and although PBS-eligible students report devoting 8% (or 13 minutes) more time to studying, the difference is not statistically significant.

In the next four rows of Table 4, we report impacts based on the 24-hour time diary. The first row reports results for hours spent on all educational activities; the next three rows present

[14] Estimates are similar if we control for baseline characteristics such as age, sex, race, and parental education.

disaggregated results for class attendance, studying, and test preparation.[15] The results suggest that eligibility for a performance-based scholarship induced participants to devote about 30 minutes more to educational activities in the prior 24-hour period than those assigned to the control group, although the difference is not statistically significant. Further, those eligible for a performance-based scholarship report spending significantly more time on test preparation (an additional 22 minutes per day) than those assigned to the control group. In general, the results provide evidence that performance-based scholarships induced eligible students to devote more effort to educationally-productive activities.

Results in the remaining columns of the table are from the California demonstration. Recall that a key difference between the CA program and that in NYC is the students in CA were randomly assigned in the spring of their senior year in high school while we surveyed them in the fall of what would be their first year attending a post-secondary institution. Focusing on the coefficients reported in column (5) of the table, we find that PBS-eligible students were 6 percentage points more likely than the control group to report ever enrolling at a post-secondary institution, a difference that is statistically significant at the 1 percent level. Further, the PBS-eligible students were 7 percentage points more likely to report attending all or most of their classes in the last 7 days and reported studying about 9 minutes more per day than those in the control group. The estimated impacts based on data from the 24-hour time diary are smaller and generally not statistically significant, with the exception that the impact on time spent preparing for tests is statistically significant at the 10 percent level. This set of results is also generally consistent with performance-based scholarships inducing students to devote more time to academic tasks.

[15] The results in the last three rows do not add up to "all educational activities" as the broader category includes additional types of educational activities such as meeting with instructors and registering for classes that are not reflected in the last three rows.

At the same time, an important dimension to the demonstration in CA was the inclusion of a treatment group that was eligible for a "regular" scholarship that did not require meeting performance benchmarks. In particular, as discussed earlier, this non-PB scholarship does not affect the marginal value of effort because payment is not tied to meeting benchmarks and is only valid for one semester. While in general we expect that the PB scholarships would have a larger impact on educational outcomes than the non-PB scholarship, one possible exception is that on ever enrolling in an institution since the non-PBS was a guaranteed payment. In contrast to this expectation, the results in columns (5) and (6) of Table 4 suggest that those eligible for a PB scholarship were about 6 percentage points more likely to ever enroll in an institution. One explanation for this result is that unlike the PB scholarships, the non-PB scholarship was paid directly to the institution rather than to the participant. As a result, the (non-PB) scholarship payment may not have been as salient to the student, or the institutions may have adjusted the student's total financial aid package in response such that there was no reduction, on average, in the net cost of college to those eligible for the non-PB scholarship. With other outcomes, we generally find (as expected) that the impacts are larger for those eligible for a PB scholarship than for those offered a non-PB scholarship, however in most cases, we are unable to detect a statistically significant difference. Tests of the difference in impact between the PB scholarships and the non-PB scholarship also potentially provide insight into whether students are responding to the incentives in the PB scholarship or the additional income. We test for this implication, below.

Before turning to how participants allocated their time to other activities, we consider two measures that may indicate ways of increasing academic effort without necessarily spending more time studying, namely, learning strategies and academic self-efficacy. As discussed above,

PBS eligibility may induce participants to concentrate more on their studies by encouraging them to employ more effective study strategies such that the time devoted to educational activities is more productive. Similarly, by raising their academic self-efficacy the scholarships may also induce students to be more engaged with their studies. Results using scales based on the MSLQ Learning Strategies index and the PALS academic self-efficacy index are presented in the last two rows of Table 4. We have standardized the variables using their respective control group means and standard deviations; as a result, the coefficients reflect impacts in standard deviation units. For both NYC and CA we estimate that eligibility for a PB scholarship had positive and statistically significant impacts on these dimensions that range from 14 to 23 percent of a standard deviation. Note as well, the impacts on learning strategies and academic self-efficacy for those in CA selected for a non-PB scholarship were substantially smaller than those selected for a PB scholarship, consistent with increased academic effort on the part of PBS-eligible individuals. Unfortunately we do not have access to grades and other measures of academic performance with which to observe the impact of these intermediate measures on more concrete academic outcomes.

Results presented thus far generally suggest that participants selected for a PB scholarship devoted more time and effort to educational activities. Given there are only 24 hours in the day, a key question is what did PBS-eligible participants spend less time doing? Table 5 presents results from three other broad time categories based on the 24-hour time diary: work, household production, and leisure and other activities.[16] In NYC we estimate that the typical participant (as represented by the control group) works about 2.5 hours per day, devotes nearly

[16] "Home production" includes time spent on personal care, sleeping, eating and drinking, performing household tasks, and caring for others. "Leisure activities" include participating in a cultural activity, watching TV/movies/listening to music, using the computer, spending time with friends, sports, talking on the phone, other leisure, volunteering, and religious activities.

12 hours to home production (which includes sleeping), and devotes about 5 hours to "leisure." We find that PBS-eligible participants accommodated spending about 30 more minutes in the last 24 hours on educational activities by devoting about 41 fewer minutes to leisure activities, an impact that is statistically significant at the 5 percent level. The participants in CA also accommodated increased time spent on educational activities by spending (statistically) significantly less time on leisure activities. We find no evidence that PB (or non-PB) scholarship eligibility induced participants to reduce time spent on work or home production; for both sites the estimated impacts are small, positive, and not statistically different from zero.

Finally, concerns about using incentives for academic achievement include the possibility of unintended consequences of the programs, such as cheating or taking easier classes to get good grades, or reducing students' internal motivation to pursue more education. In Table 6 we present impacts on several potential unintended consequences for the participants in both the NYC and CA sites. In NYC we find little systematic evidence that eligibility for a PB scholarship resulted in adverse outcomes. For example, those randomly selected for a PB scholarship were more likely to report being satisfied with life and having taken challenging classes and were less likely to report having asked for a regrade or having felt they had to cheat (only the impact on life satisfaction is statistically significant (at the 10% level)). Further, they were significantly more likely to report behavior consistent with increased internal motivation. In other words, the incentive payments did not seem to reduce their internal motivation.

In contrast, the results are more mixed in CA. For example, on the one hand those in CA who were eligible for a PB scholarship were more satisfied with life and more likely to take challenging classes compared to the control group (a difference that is statistically significant). On the other hand, PBS-eligible participants reported an increase in behavior that is consistent

with external motivation compared to both control group participants and those randomly selected for a non-PB scholarship.

Overall, the results suggest that eligibility for a scholarship that requires achieving benchmarks results in a small increase in time and effort devoted to educational activities with a decrease in time devoted to leisure. Further, there is at best mixed evidence that the same incentives result in adverse outcomes, such as cheating, "grade grubbing," or taking easier classes.

C. Impacts by Scholarship Characteristics

Two key questions are whether the size and/or duration of the potential scholarship affect the impact on student behavior and whether it is the incentive structure or the additional income that generates improvements in outcomes. Prior studies of performance-based scholarships have tended to focus on one type of scholarship of a particular duration with variation in other types of resources available to students (such as student support services or a counselor). In CA students eligible for a performance-based scholarship were also randomly assigned to scholarships of differing durations and/or sizes as well as a non-performance-based scholarship. As noted in Table 1, CA students selected for scholarship eligibility were assigned to one non-incentive scholarship worth $1,000 for one term or to one of five types of incentive scholarships that ranged from $1,000 for one term to $1,000 for each of four terms or $500 for each of two terms to $500 for each of four terms.

We present the results by scholarship characteristics in Tables 7a and 7b for CA. In Table 7a we present results in the first academic term after random assignment (fall). Impact estimates of $500/term scholarships are presented in column (1), $1,000/term scholarships in column (2),

and the non-PB scholarship in column (3). P-values for the test of equality of columns (1) and (2) coefficient estimates are presented in column (4), and those for the equality of estimates in columns (2) and (3) are presented in column (5). In Table 7b, we look at results for outcomes measured in the second semester after random assignment and consider impacts for the one term non-PB and PB scholarships that have expired and the PB scholarships for which eligibility continued two or more terms.[17]

Impacts by Size and Duration of the Scholarship

Theoretically one would expect that the larger-sized scholarships would induce increased effort during the semesters for which the students were eligible, and the longer-duration scholarships would induce students to enroll for more semesters and affect effort during those additional semesters of eligibility. As such, in the first semester after random assignment, we might expect to see a difference between scholarships worth $1,000 and those worth $500 per term; these results are presented in Table 7a. Interestingly, we do not find large differences in the effect of PB scholarship eligibility related to the size of the scholarship. Students who were eligible for a $500 per semester scholarship responded similarly on most outcomes to students who were eligible for a $1,000 per semester scholarship suggesting that larger incentive payment amounts do not lead to larger impacts on student effort.[18]

In Table 7b we test whether the impact of performance-based scholarships persisted after the incentives had expired by analyzing data from the second semester after random assignment and comparing the coefficient estimates for the one term PB scholarship (column 2) to the

[17] While we are able to test for some dimensions over which we would expect to see impacts by the characteristics of the scholarship, we also note that we only followed the students for at most two semesters after random assignment and therefore cannot test all dimensions on which the scholarship structure might matter.
[18] This result is familiar in the context of survey implementation where experimental evidence suggests that larger incentives do not increase response rates (see, e.g., James and Bolstein (1992)).

coefficient estimates for students who were still eligible for PB scholarships (column 3). The column 3 estimates are generally larger than the estimates in column (2) for students who are no longer eligible for a PB scholarship, although only the test of equality of impacts on time spent on educational activities in general (and attending class specifically) is statistically significant at traditional levels. Note as well that while the coefficient estimates suggest participants with PB eligibility in the second semester were slightly more likely to be currently enrolled than either the control group or PB scholarship students who were no longer eligible, the differences are small and not statistically different from zero. These results provide at best mixed evidence that PB scholarships influence enrollment after the first semester.[19] At the same time, given the relatively larger size of the impacts for students who continued to be eligible for a PB scholarship, they are consistent with the earlier evidence that such incentives influence behavior during semesters of eligibility; we do not find consistent evidence of persistent effects after eligibility has expired.

Incentives versus Additional Income

An important question regarding any results with performance-based scholarships is whether the impacts are driven by the additional income or by the incentive structure of the scholarship. In our study, a comparison of the (fall term) impacts of the non-PB scholarship (worth $1,000 in one term) and the PB scholarship of $1,000 in one term provides the strongest test of the potential impact of the incentive effect in the performance-based scholarship compared to an income effect. This test can be made in Table 7a by comparing the impacts of the $1,000 PB scholarships (column 2) to those of the $1,000 non-PB scholarship (column 3) in the first term (the p-values of the tests of equality are in column (5)). As expected, we generally

[19] Results in Appendix Table 3 suggest a bigger impact on second semester enrollment in NYC than in CA.

find that the PBS coefficient estimates are larger than those for the non-incentivized scholarship, especially for those outcomes for which there were larger impacts for the PB scholarship in Table 4 (such as time preparing for tests, hours per day spent studying, and the indices of learning strategies and academic self-efficacy). While in most cases the standard errors are too large to detect differences at standard levels of statistical significance, the magnitude and pattern of coefficients are consistent with students responding to the incentive structure of the scholarships rather than the additional income.

D. Impacts by Type of Participant

Finally, the theoretical model behind incentive scholarships and participant behavior suggests the scholarships should have a larger impact for participants who have a higher marginal cost of time and those who are relatively more myopic. In this section we attempt to assess whether the scholarships, indeed, have such differential impacts by type of participant. Because we do not directly observe these individual characteristics, we infer them based on background characteristics using data from NYC. In the first four columns of Table 8, we estimate whether the incentive scholarships had a greater impact on those participants who did not have young children under the age of six on the assumption that parents of young children have less flexibility with their time given their parenting responsibilities which, in turn, raises the marginal cost of their time. The coefficient estimates in column (1) represent the main effect of PBS eligibility; those in column (2) represent the interaction effect; the p-value on the interaction term is presented in column (3).

All of the estimated coefficients on the interaction term are positive in the first five rows of Table 8 indicating that the impact of the PB scholarship was larger for those without children,

as expected. For example, the estimated impacts on being prepared for the last class attended and time spent studying in the past 7 days for those without young children are more than twice the estimated impacts for those with young children. Notably, one place where eligibility for a PBS generated a larger impact for those with young children compared to those without was the indices of academic effort and self-efficacy. This may not be surprising as one might expect those who find it costly to increase the quantity of their effort to increase the quality of that effort in order to reach the scholarship benchmark(s). In all cases the interaction term is not statistically significant due to large standard errors, but the pattern of coefficients is quite suggestive.

As a second exercise, we examine if the scholarships had a larger impact on individuals who are plausibly more myopic than other participants. Not having a true measure of "myopia" we proxy for it with an indicator for individuals who had completed 11 or fewer years of schooling before completing a GED or enrolling in (community) college, again using data from NYC. While not a perfect measure of myopia, researchers have hypothesized that it is a likely explanation for high school dropout (see, e.g., Oreopoulos 2007). As such, we expect that the performance incentive will have a larger impact on those individuals who dropped out early than for those who did not. The results are in columns (5) – (8) of Table 8.

Indeed, the results are consistent with the incentive mattering more for those who discount the future greatest. For example, program group participants hypothesized to be more myopic spent significantly more time on educational activities than less myopic program participants; they were also more likely to be prepared for the last class attended and scored higher on the scale of academic self-efficacy. These differences are statistically significant at traditional levels.

While we do not have direct measures of the marginal cost of time for participants or the rates at which they discount the future, using plausible proxies for these characteristics we find evidence that the performance-based scholarships largely worked through hypothesized channels as estimated impacts were generally largest for those expected to be most affected by the incentives.

V. Conclusion

Although education policymakers have become increasingly interested in using incentives to improve educational outcomes, the evidence continues to generate, at best, small impacts, leading to the question of whether such incentives can actually change student effort toward their educational attainment. We use survey data from participants who were randomly assigned eligibility for a performance-based post-secondary scholarship to examine how incentive payments (tied to meeting enrollment, attendance, and grade point average performance benchmarks) affect a student's effort toward her studies.

As a whole, we find evidence that the performance-based scholarships increased student effort in terms of the amount and quality of time spent on educational activities and that the additional time spent on education comes at the expense of time spent on leisure activities. We also find that the change in effort likely comes from the incentive structure of the scholarships rather than the additional income. As predicted, the incentives seem to have a larger impact on individuals who have greater ability to reallocate time use (individuals without young children) and on individuals who are more myopic. Taken together, these results suggest that post-secondary students can, and do, respond to monetary incentives, on average.

The question remains, however, whether these observed changes in effort are large enough to generate meaningful improvements in measures of academic achievement, such as grades and educational attainment. Our estimates suggest that the scholarships induced students to spend an additional 10 to 30 minutes per day (or roughly 1-3.5 hours more per week) on educational activities. Studies of the relationship between GPA and time spent studying outside of class find that increased study time has a positive effect on GPA (See Plant et al. 2005 and Stinebrickner and Stinebrickner 2007.).[20] Using the instrumental variable estimates in Stinebrickner and Stinebrickner (2007) for a back-of-the-envelope calculation, the additional time spent on educational activities by the PBS eligible students translates into as much as an increase of 0.18 grade points.[21] This implied impact on GPA is roughly similar to that estimated in Barrow et al. (2012) further suggesting its plausibility although we note that the incentive-based scholarship program and population studied is not the same as in this study. As such, our results are consistent with the impacts of incentives on short-run academic outcomes observed in the literature that do not necessarily result in longer-run impacts on persistence and credit accumulation. Importantly, however, our results suggest that students can, and will, change their behavior in response to incentives, and while such changes may only result in small improvements in educational attainment, results from Barrow et al. (2012) suggest that such interventions may nonetheless be cost effective.

[20] Some studies also examine the relationship between class attendance and GPA although class attendance is generally measured in terms of percentage of classes attended rather than time spent in class.

[21] Stinebrickner and Stinebrickner (2007) estimate that an additional 1 hour of study time is associated with an increase in GPA of 0.29 to 0.36 grade points, representing 50 percent of the observed standard deviation in first term GPA. (Mean GPA in their study is 3.00 with a standard deviation of 0.65.)

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Table 2: Total (Baseline) Sample Size by Site

	NYC	CA					
	PBS	Non-PBS	PBS				
	$1,300/term	($1,000)	$ 500/term		$1000/term		
Cohort	2 or 3 terms	1 term	2 terms	4 terms	1 term	2 terms	4 terms
Fall 2008	368						
Spring 2009	514						
Fall 2009	619	483	484	447	468	468	460
Fall 2010		653	637	679	611	633	637
Total	1,501	1,136	1,121	1,126	1,079	1,101	1,097

Notes: The NYC sample size includes both those assigned to "regular" PBS scholarship and those assigned to the "regular" PBS scholarship and the summer scholarship. Sample sizes for CA include 1,500 individuals added to the control group.

Table 3: Characteristics of PBS Participants and First-year Students in the National Postsecondary Student Aid Study (NPSAS) of 2008

Characteristics	NYC PBS	NPSAS 2-Year Public Colleges	CA PBS	NPSAS All Types of Institutions
	(1)	(2)	(3)	(4)
Age (years)	26.5	26.988	17.6	18.438
Age 17-18 (%)			96.7	60.1
Age 19-20 (%)			3.2	39.9
Age 21-35 (%)	99.9	96.2	0	
Female (%)	69.1	52.1	59.9	53.5
Race/ethnicity (%)				
Hispanic	44.3	21.6	63.1	15.4
Black	37.2	18.8	3.9	12.3
Asian	9.7	7.1	10.6	5.5
Native American	0.2	1.9	0.7	0.9
Other	1.0	1.8	0.5	4
Children				
Has any children (%)	47.8	46.9		2.4
Number of children	0.8	1.823		1.32
Household Size		2.562		3.933
Financially dependent on parents (%)	1.3	11.9		94.7
Education				
Years since high school		6.958		0.135
Enrolled to complete certificate program	2.9	12.1		
Enrolled to transfer to 4-year college	43.1	32.1		
Highest degree completed				
GED	33.1	19.9		2.4
High School Diploma	65.0	54.1		90.8
Technical certificate or AA	15.2	19.3		3.6
First family member to attend college (%)	32.9	43.1	54.8	27.8
Highest degree by either parent (%)				
Did not complete High School	24.2	13.4	36.4	4.1
High School Diploma or Equivalent	32.9	33.6	30.3	24.6
Some college including tech certificate	16.1	18.9		
Associate's or similar degree	6.4	8.5		
Some college including technical certificate, AA degree			22.3	27.4
4-year bachelor's degree or higher	20.3	25.6	11.1	43.9
U.S. citizen		88.6		95.5
Non-English spoken at home	54.6	20.8	63.0	11.8
Number of observations	1,501	960	6,660	12,790

Notes: Based on authors' calculations from MDRC data and data from the U.S. Department of Education's 2008 National Postsecondary Student Aid Study (NPSAS) of 2008. We limit the NPSAS data to first-time students. For comparability with the PBS New York sample we limit the sample to students aged 22 to 36 attending public two-year colleges column (2) and for comparability with the PBS California sample we include students aged 16-20 who are attending any type of institution. The NPSAS means are weighted by 2008 study weight.

Table 4: Impact on Educational Outcomes in NYC and CA

	NYC			CA				
	Control Mean	PBS Impact	Obs	Control Mean	PBS Impact	Non-PBS Impact	p-value PBS=Non-PBS	Obs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ever attended postsecondary institution	0.922	-0.012	613	0.831	0.059***	-0.003	0.058	2,872
		(0.023)			(0.016)	(0.031)		
Attended most/all classes in last 7 days	0.778	0.062*	613	0.776	0.072***	0.031	0.258	2,872
		(0.032)			(0.018)	(0.035)		
Prepared for last class attended	0.810	0.026	606	0.736	0.080***	0.026	0.172	2,861
		(0.032)			(0.019)	(0.037)		
Hours per day spent studying last 7 days	2.843	0.217	611	2.936	0.159	0.027	0.534	2,871
		(0.204)			(0.101)	(0.202)		
Hours per day spend on:								
All educational activities	4.504	0.470	613	4.757	0.174	0.249	0.842	2,874
		(0.314)			(0.179)	(0.358)		
Attending class	1.883	0.018	613	1.861	0.029	0.117	0.671	2,874
		(0.195)			(0.098)	(0.196)		
Studying/homework	1.745	0.070	613	2.242	0.004	0.009	0.986	2,874
		(0.185)			(0.118)	(0.236)		
Preparing for tests	0.766	0.368**	613	0.552	0.126*	0.096	0.847	2,874
		(0.171)			(0.074)	(0.147)		
MSLQ Index	0	0.225***	613	0	0.224***	0.043	0.047	2,871
		(0.078)			(0.043)	(0.087)		
Academic Self-Efficacy	0	0.189**	610	0	0.137***	0.013	0.169	2,866
		(0.078)			(0.043)	(0.086)		

Note: "All educational activities" includes attending classes (traditional or online), studying or doing homework, preparing for tests, and other activities related to schooling. * indicates statistical significance at the 10% level; ** indicates statistcal significance at the 5% level; and *** indicates statistical significance at the 1% level. The MSLQ Index and Academic Self-Efficacy variables have been standardized to the mean and standard deviation of the relevant control group.

Table 5: Impact on Time Use in past 24 hours in NYC and CA

	NYC		CA			
Hours per day spent on:	Control Mean (1)	PBS Impact (2)	Control Mean (3)	PBS Impact (4)	Non-PBS Impact (5)	p-value PBS=Non-PBS (6)
Work	2.496	0.096	0.750	0.037	0.060	0.904
		(0.299)		(0.091)	(0.183)	
Household Production	11.89	0.118	11.72	0.160	-0.032	0.551
		(0.352)		(0.153)	(0.306)	
Leisure and other activities	5.080	-0.689**	6.765	-0.385**	-0.279	0.762
		(0.302)		(0.166)	(0.331)	

Note: "Household Production" includes personal care, sleep, eating and drinking, performing household tasks, and caring for others. "Leisure and other activities" includes leisure, commuting, and extracurricular activities. The number of observations in NYC=613 and in CA=2,874. * indicates statistical significance at the 10% level; ** indicates statistcal significance at the 5% level; and *** indicates statistical significance at the 1% level.

Table 6: Estimates of Potential "Unintended" Consequences in NYC and CA

	NYC			CA				
	Control Mean	PBS Impact	Obs	Control Mean	PBS Impact	Non-PBS Impact	p-value PBS=Non-PBS	Obs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Very satisfied or satisfied with life	0.494	0.070*	608	0.624	0.013	-0.002	0.742	2,850
		(0.041)			(0.021)	(0.042)		
Strongly agree/agree take challenging classes	0.451	0.024	607	0.385	0.065***	0.026	0.387	2,856
		(0.041)			(0.021)	(0.043)		
Ever asked for regrade	0.262	-0.018	609	0.197	0.010	-0.093***	0.005	2,860
		(0.036)			(0.017)	(0.035)		
Ever felt had to cheat	0.176	-0.027	611	0.349	-0.089***	-0.088**	0.978	2,854
		(0.030)			(0.020)	(0.040)		
External Motivation	0	0.031	558	0	0.088*	-0.064	0.120	2,417
		(0.088)			(0.046)	(0.094)		
Internal Motivation	0	0.195**	560	0	0.047	-0.095	0.158	2,419
		(0.076)			(0.048)	(0.096)		

Note: * indicates statistical significance at the 10% level; ** indicates statistcal significance at the 5% level; and *** indicates statistical significance at the 1% level. The External and Internal Regulation variables have been standardized to the mean and standard deviation of the relevant control group.

Table 7a: Effects on Educational Outcomes in CA in the First Semester, by Amount of Scholarship

	$500/T	$1,000/T	Non-PBS	p-value 500/T=1000/T	p-value Non-PBS=1000/T	Obs
	(1)	(2)	(3)	(4)	(5)	(6)
Ever attended postsecondary institution	0.078***	0.046**	-0.003	0.236	0.153	2,872
	(0.022)	(0.019)	(0.031)			
Currently enrolled in postsecondary institution	0.073***	0.059***	0.027	0.613	0.386	2,873
	(0.024)	(0.020)	(0.033)			
Attended most/all classes in last 7 days	0.082***	0.066***	0.031	0.597	0.365	2,872
	(0.025)	(0.021)	(0.035)			
Prepared for last class attended (%)	0.089***	0.073***	0.026	0.609	0.256	2,861
	(0.027)	(0.023)	(0.037)			
Hours per day spent studying in last 7 days	0.039	0.242*	0.027	0.241	0.337	2,871
	(0.144)	(0.123)	(0.202)			
Hours per day spent on:						
All educational activities	0.180	0.170	0.249	0.975	0.843	2,874
	(0.255)	(0.219)	(0.358)			
Attending class	0.175	-0.071	0.116	0.142	0.387	2,874
	(0.140)	(0.120)	(0.196)			
Studying/homework	-0.002	0.009	0.009	0.957	1.000	2,874
	(0.168)	(0.144)	(0.236)			
Preparing for tests	-0.026	0.231***	0.096	0.0398	0.406	2,874
	(0.104)	(0.090)	(0.147)			
MSLQ Index	0.241***	0.212***	0.043	0.694	0.0785	2,871
	(0.062)	(0.053)	(0.087)			
Academic Self-Efficacy	0.151**	0.127**	0.013	0.745	0.229	2,866
	(0.061)	(0.052)	(0.086)			

Note: "All educational activities" includes attending classes (traditional or online), studying or doing homework, preparing for tests, and other activities related to schooling. * indicates statistical significance at the 10% level; ** indicates statistcal significance at the 5% level; and *** indicates statistical significance at the 1% level. The MSLQ Index and Academic Self-Efficacy variables have been standardized to the mean and standard deviation of the relevant control group.

Table 7b: More Effects on Educational Outcomes in CA in the Second Semester, by Length of Scholarship

	Non-PBS	1 Term	2+ Terms	p-value Non-PBS=1Term	p-value 1Term=2Terms	Obs
	(1)	(2)	(3)	(4)	(5)	(6)
Ever attended postsecondary institution	-0.007	0.046	0.008	0.194	0.225	2,743
	(0.031)	(0.029)	(0.015)			
Currently enrolled in postsecondary institution	0.002	0.006	0.012	0.933	0.872	2,741
	(0.034)	(0.033)	(0.017)			
Attended most/all classes in past 7 days	0.018	0.014	0.039*	0.938	0.544	2,740
	(0.040)	(0.038)	(0.020)			
Prepared for last class attended (%)	0.020	0.040	0.042**	0.689	0.946	2,711
	(0.038)	(0.036)	(0.019)			
Hours per day spent studying in last 7 days	-0.363	0.191	0.019	0.0744	0.466	2,739
	(0.234)	(0.221)	(0.118)			
Hours per day spent on:						
All educational activities	-0.232	-0.264	0.526***	0.951	0.0495	2,743
	(0.396)	(0.376)	(0.200)			
Attending class	-0.058	-0.291	0.144	0.434	0.0563	2,743
	(0.224)	(0.213)	(0.113)			
Studying/homework	-0.219	0.129	0.273**	0.270	0.552	2,743
	(0.237)	(0.225)	(0.120)			
Preparing for tests	-0.031	-0.112	0.117	0.741	0.220	2,743
	(0.184)	(0.174)	(0.093)			
MSLQ Index	0.088	0.215**	0.163***	0.308	0.583	2,742
	(0.094)	(0.089)	(0.047)			
Academic Self-Efficacy	0.053	0.051	0.085*	0.983	0.725	2,741
	(0.095)	(0.090)	(0.048)			

Note: "All educational activities" includes attending classes (traditional or online), studying or doing homework, preparing for tests, and other activities related to schooling. * indicates statistical significance at the 10% level; ** indicates statistcal significance at the 5% level; and *** indicates statistical significance at the 1% level. The MSLQ Index and Academic Self-Efficacy variables have been standardized to the mean and standard deviation of the relevant control group.

Table 8: Impacts by Parental Status and Educational Attainment, NYC

	Impact by Parent of Young Children				Impact by Years of Education			
	PBS	PBS*No Children <6	p-value of interaction	Obs	PBS	PBS * <11 Yrs Ed	p-value of interaction	Obs
	(1)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Ever enrolled in post-secondary insitution	-0.051	0.059	0.225	609	-0.014	0.029	0.570	570
	(0.039)	(0.048)			(0.029)	(0.051)		
Attended most/all classes in last 7 days	0.056	0.003	0.960	609	0.064	0.038	0.597	570
	(0.054)	(0.067)			(0.040)	(0.071)		
Prepared for last class attended	-0.041	0.102	0.125	602	-0.018	0.132*	0.0602	564
	(0.054)	(0.067)			(0.039)	(0.070)		
Hours per day spent studying in past 7 days	0.098	0.132	0.760	607	0.204	-0.035	0.937	569
	(0.347)	(0.431)			(0.245)	(0.438)		
Hours per day spent on all educational activities	0.311	0.098	0.882	609	0.104	1.497**	0.0317	570
	(0.530)	(0.659)			(0.390)	(0.695)		
MSLQ Index	0.309**	-0.151	0.356	609	0.121	0.300*	0.0841	570
	(0.132)	(0.163)			(0.097)	(0.174)		
Academic Self-Efficacy	0.191	-0.031	0.849	606	0.066	0.398**	0.0222	568
	(0.133)	(0.165)			(0.098)	(0.174)		

Note: "All educational activities" includes attending classes (traditional or online), studying or doing homework, preparing for tests, and other activities related to schooling. * indicates statistical significance at the 10% level; ** indicates statistcal significance at the 5% level; and *** indicates statistical significance at the 1% level. The MSLQ Index and Academic Self-Efficacy variables have been standardized to the mean and standard deviation of the relevant control group.

Appendix Table 1a: Randomization of Program and Control Groups at NYC Sites

Baseline Characteristics	Random Assigment: Program Group	Random Assigment: Control Group	p-value of difference	N
Age (years)	26.5	26.6	0.713	1501
Married, living with spouse	11.1	13.8	0.129	1384
Married, not living with spouse	7.4	7.19	0.916	1384
Not married, lving with partner	12.1	10.1	0.206	1384
Single	69.3	68.9	0.87	1384
Female (%)	69.8	68.4	0.568	1501
No Children Under 6 (%)	69.1	65.5	0.119	1492
Race/ethnicity (%)				
Hispanic	44.4	44.2	0.995	1468
Black	36.2	38.2	0.419	1468
White	6.3	5.9	0.736	1468
Asian	10.3	9	0.381	1468
Native American	0.1	0.3	0.569	1468
Other	1	1.1	0.791	1468
Multi-racial	1.79	1.2	0.4	1468
Race not reported	2.5	1.89	0.395	1501
Household receiving benefits (%)				
Receiving any government benefit	42.2	43.9	0.528	1321
Receiving nemployment insurance	7.69	11.5	0.017	1321
Household receiving SSI	6.59	6.09	0.703	1321
Household receiving TANF	9.19	6.9	0.123	1321
Household receiving food stamps	30.1	30.2	0.959	1321
Public housing or section 8 housing	10.6	10.6	0.999	1321
Financially dependent on parents (%)	1	1.7	0.231	1435
Currently employed (%)	56.5	55.4	0.648	1446
Years since HS	6.8	6.9	0.851	1375
High school diploma or GED	96.5	96.5	0.884	1470
Tech certificate	11.8	14.8	0.082	1470
Last attended 11th grade or lower	29.5	31.7	0.345	1408
First family member to attend college (%)	34.5	31.2	0.194	1454
Main reason for enrolling in college (%)				
Complete certification program	3	2.79	0.89	1478
Obtain AA	48.5	52.7	0.104	1478
Transfer to 4-year college	46	40	0.017	1478
Obtain job skills	2.79	3.7	0.375	1478
Other reason	1.2	2	0.204	1478
Primary language (%)				
English	45.5	45.2	0.885	1487
Spanish	29	29.8	0.717	1487
Other Language	54.4	54.7	0.885	1487

SOURCE: Calculations using Baseline Information Form (BIF) data.
NOTES: Means have been adjusted by research cohort and site. An omnibus F-test of whether baseline characteristics jointly predict research group status yielded a p-value of 0.68. Distributions may not add to 100 percent because of rounding. Respondents that reported being Hispanic/Latino and also reported a race are included only in the Hispanic category. Respondents that are not coded as Hispanic and chose more than one race are coded as multi-racial.

Appendix Table 1b: Randomization of Program and Control Groups at CA Sites

	Random Assignment		p-value of	
	Program Group	Control Group	difference	N
Age (years)	17.6	17.6	0.643	6660
Female (%)	60	59.7	0.735	6659
Race/ethnicity (%)				
Hispanic	63.2	63	0.999	6597
Black	3.9	3.9	0.91	6597
White	18.1	19	0.189	6597
Asian	10.6	10.6	0.97	6597
Native American	0.699	0.699	0.731	6597
Other	0.699	0.2	0.01	6597
Multi-racial	2.7	2.4	0.314	6597
Race not reported	1	0.899	0.843	6660
Parent/s highest level of education completed (%)				
No High School Diploma	36.4	36.2	0.902	6541
High School Diploma/GED	29.3	31.1	0.141	6541
Associate's or similar degree	23.1	21.6	0.134	6541
Bachelor's Degree	11.1	11	0.962	6541
First family member to attend college (%)	55.7	54.7	0.398	6612
Primary language (%)				
English	37.2	36.7	0.551	6617
Spanish	50.9	51.5	0.448	6617
Other Language	62.7	63.2	0.551	6617

SOURCE: Calculations using Baseline Information Form (BIF) data.

NOTES: Notes: The means have been adjusted by research cohort and site. An omnibus F-test of whether baseline characteristics jointly predict research group status yielded a p-value of 0.55. Distributions may not add to 100 percent because of rounding. Respondents that reported being Hispanic/Latino and also reported a race are included only in the Hispanic category. Respondents that are not coded as Hispanic and chose more than one race are coded as multi-racial.

Appendix Table 2a: Random Assignment of Program and Control Groups at NYC sites, Analysis Sample

	Random Assignment		p-value of difference	N
	Program Group	Control Group		
Age (years)	26.3	26.7	0.375	613
Marital Status (%)				
Married, living with spouse	12.8	13.3	0.825	559
Married, not living with spouse	7.19	9.6	0.326	559
Not married, lving with partner	12.8	7.9	0.068	559
Single	67.1	69	0.633	559
Female (%)	71.9	75.5	0.326	613
No Children Under 6 (%)	69	61.7	0.061	609
Race/ethnicity (%)				
Hispanic	43.4	44.4	0.81	598
Black	38.4	40.5	0.582	598
White	5.59	5	0.741	598
Asian	10	6.09	0.087	598
Native American	0	0		598
Other	0.899	1.2	0.722	598
Multi-racial	1.7	2.79	0.405	598
Race not reported	2.59	2.29	0.814	613
Household receiving benefits (%)				
Receiving any government benefit	47.2	51.2	0.36	543
Unemployment insurance	9.1	16.3	0.009	543
Household receiving SSI	6.4	6.09	0.885	543
Household receiving TANF	8.8	8.89	0.961	543
Household receiving food stamps	33.2	36.5	0.43	543
Public housing or section 8 housing	12.6	12	0.852	543
Financially dependent on parents (%)	0.899	1.6	0.409	592
Currently employed (%)	53.2	52	0.764	589
Years since HS	6.69	6.8	0.816	566
High school diploma or GED (%)	96.5	97.3	0.62	600
Tech certificate (%)	13.5	13.3	0.972	600
Last attended 11th grade or lower (%)	29.7	32.7	0.435	570
First family member to attend college (%)	36.2	29.2	0.075	597
Main reason for enrolling in college (%)				
Complete certification program	3.2	2.7	0.763	605
Obtain AA	50.2	53.7	0.381	605
Transfer to 4-year college	45.2	39.4	0.15	605
Obtain job skills	2.79	3.59	0.598	605
Other reason	1.39	0.8	0.432	605
Primary language (%)				
English	43.4	43.4	0.986	606
Spanish	31.3	32.5	0.768	606
Other Language	56.5	56.5	0.986	606

SOURCE: Calculations using Baseline Information Form (BIF) data.
Notes: The means have been adjusted by research cohort and site. An omnibus F-test of whether baseline characteristics jointly predict research group status yielded a p-value of 0.63. Distributions may not add to 100 percent because of rounding. Respondents that reported being Hispanic/Latino and also reported a race are included only in the Hispanic category. Respondents that are not coded as Hispanic and chose more than one race are coded as multi-racial.

Appendix Table 2b: Randomization of Program and Control Groups at CA Sites, Analysis Sample

	Random Assignment		p-val of difference	N
	Program Group	Control Group		
Age (years)	17.6	17.6	0.116	2874
Female (%)	62.7	63.9	0.523	2874
Race/ethnicity (%)				
Hispanic	62	62	0.984	2847
Black	3.4	3.29	0.875	2847
White	18	18.7	0.512	2847
Asian	12.1	12.6	0.6	2847
Native American	0.4	0.4	0.795	2847
Other	0.6	0.3	0.277	2847
Multi-racial	3.29	2.29	0.127	2847
Race not reported	0.8	1	0.628	2874
Parent/s highest level of education completed (%)				
No High School Diploma	37.5	38	0.813	2837
High School Diploma/GED	28.3	28.7	0.832	2837
Associate's or similar degree	23.5	21.5	0.246	2837
Bachelor's Degree	10.6	11.6	0.374	2837
First family member to attend college (%)	54.4	55	0.782	2860
Primary language (%)				
English	35	34.5	0.762	2860
Spanish	51.4	51.9	0.746	2860
Other Language	64.9	65.4	0.762	2860

SOURCE: Calculations using Baseline Information Form (BIF) data.

Notes: The means have been adjusted by research cohort and site. An omnibus F-test of whether baseline characteristics jointly predict research group status yielded a p-value of 0.77. Distributions may not add to 100 percent because of rounding. Respondents that reported being Hispanic/Latino and also reported a race are included only in the Hispanic category. Respondents that are not coded as Hispanic and chose more than one race are coded as multi-racial.

Appendix Table 3: Impact on Education Outcomes in NYC, by Scholarship Type

	PBS	PBS + Summer Treatment	p-value PBS = PBS+Summer	Obs
	(1)	(2)	(3)	(4)
First Semester After Random Assignment				
Currently attending postsecondary institution	0.004	0.042	0.424	277
	(0.044)	(0.044)		
Attended most/all classes in last 7 days	0.069	0.093*	0.683	277
	(0.054)	(0.055)		
Prepared for last class attended	-0.045	0.037	0.183	274
	(0.056)	(0.057)		
Hours per day studying in last 7 days	-0.077	0.333	0.262	276
	(0.333)	(0.338)		
Hours per day spend on all educational activities	0.612	0.914	0.643	277
	(0.593)	(0.603)		
MSLQ Index	0.177	0.134	0.759	277
	(0.129)	(0.131)		
Academic Self-Efficacy	0.272*	0.172	0.517	275
	(0.139)	(0.143)		
Second Semester After Random Assignment				
Currently attending postsecondary institution	0.108*	0.024	0.220	208
	(0.063)	(0.063)		
Attended most/all classes in last 7 days	0.063	0.031	0.689	208
	(0.074)	(0.074)		
Prepared for last class attended	0.077	-0.029	0.165	206
	(0.070)	(0.070)		
Hours per day studying in last 7 days	0.196	-0.098	0.551	208
	(0.450)	(0.448)		
Hours per day spend on all educational activities	1.519**	1.377*	0.854	208
	(0.703)	(0.701)		
MSLQ Index	0.025	-0.103	0.479	208
	(0.165)	(0.164)		
Academic Self-Efficacy	0.064	-0.126	0.248	208
	(0.150)	(0.150)		

Note: The data in this table derive only from cohort 2 in NYC . "All educational activities" includes attending classes (traditional or online), studying or doing homework, preparing for tests, and other activities related to schooling. * indicates statistical significance at the 10% level; ** indicates statistcal significance at the 5% level; and *** indicates statistical significance at the 1% level. The MSLQ Index and Academic Self-Efficacy variables have been standardized to the mean and standard deviation of the relevant control group.

Appendix Table 4a: Effects on Educational Outcomes in CA in the First Semester, by Treatment Type

	Non-PBS	$1000/1T	$500/2T	$1000/2T	$500/4T	$1000/4T	p-value 1000/1T=500/2T	p-value 1000/2T=500/4T	Obs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Ever attended postsecondary institution	-0.003	0.050	0.082***	0.073**	0.073**	0.015	0.451	0.982	2,872
	(0.031)	(0.031)	(0.031)	(0.030)	(0.030)	(0.030)			
Currently enrolled in postsecondary institution	0.027	0.058*	0.097***	0.098***	0.051	0.020	0.382	0.278	2,873
	(0.033)	(0.034)	(0.033)	(0.032)	(0.032)	(0.033)			
Attended most/all classes in last 7 days	0.031	0.065*	0.102***	0.096***	0.062*	0.036	0.431	0.458	2,872
	(0.035)	(0.035)	(0.035)	(0.034)	(0.034)	(0.034)			
Prepared for last class attended (%)	0.026	0.060	0.062*	0.105***	0.115***	0.053	0.971	0.829	2,861
	(0.037)	(0.037)	(0.037)	(0.036)	(0.036)	(0.036)			
Hours per day spent studying in last 7 days	0.029	0.149	0.069	0.539***	0.012	0.028	0.771	0.0455	2,871
	(0.202)	(0.203)	(0.199)	(0.196)	(0.194)	(0.197)			
Hours per day spent on:									
All educational activities	0.248	-0.442	0.490	0.226	-0.111	0.682*	0.0544	0.470	2,874
	(0.358)	(0.359)	(0.351)	(0.346)	(0.343)	(0.349)			
Attending class	0.117	-0.077	0.443**	-0.210	-0.080	0.073	0.0499	0.611	2,874
	(0.196)	(0.197)	(0.192)	(0.190)	(0.188)	(0.191)			
Studying/homework	0.006	-0.479**	0.030	0.032	-0.030	0.439*	0.111	0.840	2,874
	(0.236)	(0.237)	(0.232)	(0.228)	(0.226)	(0.230)			
Preparing for tests	0.097	0.121	-0.040	0.387***	-0.012	0.176	0.415	0.0367	2,874
	(0.147)	(0.147)	(0.144)	(0.142)	(0.141)	(0.143)			
MSLQ Index	0.044	0.211**	0.203**	0.278***	0.277***	0.147*	0.951	0.992	2,871
	(0.087)	(0.087)	(0.085)	(0.084)	(0.083)	(0.084)			
Academic Efficacy	0.014	0.081	0.137	0.246***	0.164**	0.049	0.629	0.465	2,866
	(0.086)	(0.086)	(0.084)	(0.083)	(0.082)	(0.084)			

Note: "All educational activities" includes attending classes (traditional or online), studying or doing homework, preparing for tests, and other activities related to schooling. * indicates statistical significance at the 10% level; ** indicates statistcal significance at the 5% level; and *** indicates statistical significance at the 1% level. The MSLQ Index and Academic Self-Efficacy variables have been standardized to the mean and standard deviation of the relevant control group.

Appendix Table 4b: Effects on Educational Outcomes in CA in the Second Semester, by Treatment Type

	Non-PBS	$1000/1T	$500/2T	$1000/2T	$500/4T	$1000/4T	p-value 1000/1T=500/2T	p-value 1000/2T=500/4T	Obs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Ever attended postsecondary institution	-0.007	0.046	-0.006	-0.010	0.036	0.011	0.176	0.223	2,743
	(0.031)	(0.029)	(0.027)	(0.029)	(0.027)	(0.029)			
Currently enrolled in postsecondary institution	0.002	0.006	0.003	-0.019	0.041	0.020	0.939	0.164	2,741
	(0.034)	(0.033)	(0.031)	(0.032)	(0.031)	(0.032)			
Attended most/all classes in last 7 days	0.019	0.014	0.060*	-0.007	0.092**	0.003	0.362	0.0476	2,740
	(0.040)	(0.038)	(0.036)	(0.038)	(0.036)	(0.038)			
Prepared for last class attended (%)	0.020	0.040	0.007	0.050	0.101***	0.009	0.493	0.287	2,711
	(0.038)	(0.036)	(0.034)	(0.036)	(0.034)	(0.036)			
Hours per day spent studying in last 7 days	-0.360	0.189	-0.139	0.087	0.265	-0.153	0.260	0.538	2,739
	(0.234)	(0.221)	(0.208)	(0.217)	(0.207)	(0.218)			
Hours per day spent on:									
All educational activities	-0.235	-0.265	0.438	0.236	0.641*	0.786**	0.157	0.412	2,743
	(0.396)	(0.376)	(0.354)	(0.370)	(0.353)	(0.370)			
Attending class	-0.060	-0.292	0.032	-0.021	0.219	0.348*	0.250	0.389	2,743
	(0.225)	(0.213)	(0.200)	(0.209)	(0.200)	(0.209)			
Studying/homework	-0.222	0.129	0.177	0.070	0.329	0.519**	0.872	0.379	2,743
	(0.237)	(0.225)	(0.212)	(0.221)	(0.211)	(0.221)			
Preparing for tests	-0.030	-0.112	0.242	0.173	0.093	-0.050	0.125	0.725	2,743
	(0.184)	(0.174)	(0.164)	(0.171)	(0.164)	(0.171)			
MSLQ Index	0.089	0.215**	0.172**	0.196**	0.192**	0.089	0.712	0.976	2,742
	(0.094)	(0.089)	(0.084)	(0.088)	(0.084)	(0.088)			
Academic Efficacy	0.053	0.051	0.055	0.070	0.120	0.092	0.969	0.673	2,741
	(0.095)	(0.090)	(0.085)	(0.088)	(0.084)	(0.088)			

Note: "All educational activities" includes attending classes (traditional or online), studying or doing homework, preparing for tests, and other activities related to schooling. * indicates statistical significance at the 10% level; ** indicates statistcal significance at the 5% level; and *** indicates statistical significance at the 1% level. The MSLQ Index and Academic Self-Efficacy variables have been standardized to the mean and standard deviation of the relevant control group.