1%(5 :25.,1* 3$3(5 6(5,(6

7+(())(&76 2) $1 ,1&(17,9(%$6(' +,*+ 6&+22/ ,17(59(17,21
21 &2//(*(287&20(6

& .LUDER -DFNVRQ

:RUNLQJ 3DSHU
KWWS ZZZ QEHU RUJ SDSHUV Z

1$7,21$/ %85($8 2) (&2120,& 5(6($5&+
0DVVDFKXVHWWV $YHQXH
&DPEULGJH 0$
)HEUXDU\

7KLV SDSHU LQWHJUDWHV PDWHULDO LQFRUSRUDWHG LQ -DF
IRU WKLV SURMHFW IURP WKH 6SHQFHU)RXQGDWLRQ 7KH D
RI $3 6WUDWHJLHV 1LQD 7D\ORU 3HUU\ :LHLULFK DQG 6KDZ
DQG 6XVDQ %URZQ DQG .DWK\ &R[RI WKH 7H[DV +LJKHU (GXFDWLRQ

7KH (IIHFWV RI DQ ,QFHQWLYH %DVHG +LJK 6FKRRO ,QWHUY

& .LUDER -DFNVRQ

1%(5 :RUNLQJ 3DSHU 1R
)HEUXDU\ 5HYLVHG)HEUXDU\
-(/ 1R , , , - -

ABSTRACT

, DQDO\]H WKH HIIHFWV RI D SURJUDP WKDW SD\V ERWK WK D
VFRUHV RQ $GYDQFHG 3ODFHPHQW H[DPV RQ FROOHJH RXWFRP
, ILQG WKDW DIIHFWHG VWXGHQWV RI DOO HWKQLFLWLHV DWW
*3$V DQG DUH PRUH OLNHO\ WR UHPDLQ LQ FROOHJH EH\RQ
LPSURYHV FROOHJH RXWFRPHV HYHQ IRU WKRVH VWXGHQWV

College matriculation and completion rates for low-income and ethnic-minority students in the United States are much lower than those for affluent whites.[1] These disparities are sobering because much of the differences in wages between whites and minorities can be attributed to differences in skills prior to labor market entry (Neal and Johnson 1996).[2] While there are differences in college going across groups, much of the gaps in educational attainment across sociodemographic groups occur among those who enter college but do not persist (Adelman 1999, Bowen and Bok 1998, Jencks and Phillips 1998).[3] Because academic preparedness is key to college success (Tinto 1993, Kalsner 1991) policies that improve scholastic ability of low-income and ethnic-minority students before college entry may reduce these differences in college enrollment and college persistence across groups.

Early educational interventions have been found to have large effects on adult outcomes (Currie 2001, Deming 2009) and some argue that that remediation of inadequate early investments is difficult and costly (Cunha and Heckman 2007, Cunha, Heckman and Lochner 2006). However, if academic underperformance is a result of some economic inefficiency (such as imperfect information, student myopia, suboptimal teacher or student effort), late interventions that alleviate such inefficiency could be very cost effective. While there are numerous programs aimed at high school students with the aim of

Advanced Placement Incentive Program (APIP) targeted primarily to low-income, minority-majority school districts with a view towards improving college-readiness. New Mexico and New York City have adopted similar programs while schools in Arkansas, Alabama, Connecticut, Kentucky, Massachusetts and Virginia have replicated the APIP.[6] Using school-level data, Jackson (2010) finds that the APIP increases AP participation, improves SAT and ACT performance and may increase college enrollment. The rich student-level data employed in this study allow me to account for student selection, and tests for the underlying mechanisms, providing a more conclusive analysis. Moreover, this study builds on Jackson (2010) by analyzing the effect of the APIP on important longer-run college outcomes.

I investigate how the APIP, which affected 11th and 12 grade students, affected (1) their college attendance (2) sophomore year college persistence (3) college GPA and (4) college completion. I link Texas high-school data to administrative Texas college records, allowing me to compare the college outcomes of students exposed to the APIP to those of students not exposed to the APIP, if they attended college in Texas.[7] Because the administrators of the APIP did not roll out the program to all interested high-schools at once, there is variation in the timing of APIP adoption within the sample of interested schools. This allows for a difference-in-difference strategy, comparing the change in outcomes between observationally similar students from the same high-school before and after APIP adoption to the change in outcomes across cohorts from other high-schools that did not adopt the APIP over the same time period. Comparing cohorts from the same high-school removes (1) the differences in unobserved attributes that make one student take AP courses while another does not and (2) the differences in unobserved attributes that make students from certain schools more likely to excel at college than others. Using changes at similar schools over the same time period as a comparison removes the effects of state policies and influences that may coincide with adoption at some schools.

While the identification strategy removes several sources of bias, there are three remaining endogeneity concerns. The first is that APIP adoption may be endogenous. To address this, I limit the sample to schools that ever adopt the APIP, with similar levels of motivation. The timing of adoption within this sub-sample is determined by the idiosyncratic preferences and

[6] Lyon Medina and Mathews http www nationalmathandscience org

[7] These data also allow me to account for selection to college, a source of bias in many studies on the pre-college determinants of college success (Breland 1979, Camara and Echternacht 2001).

availability of private donors. Supporting this assertion, I show that outcomes change after adoption, conduct falsification tests on other school and principal inputs, and show that the results are robust to including school-specific trends. The second concern is that students may select to schools. I address this in three ways. First, I define "intention to treat" based on enrollment in 10th grade rather than actual enrollment in 11th and 12th grade. Second, I show that the results are robust to eliminating students from non-feeder middle-schools, and making inferences within students who attended both the same middle- and high school. Lastly, I show that there is little empirical evidence of selective migration. The last concern is that with Texas college data only, shifting from out-of-state to in-state colleges as a result of the APIP would look like improved outcomes. To address this concern, using National Student Clearinghouse data I show that APIP adoption increases in-state, but not out-of-state, college going. In sum, I am reasonably confident that the estimates presented reflect a real causal effect.

While secondary school interventions may improve contemporaneous student outcomes and increase college-going,[8] there are a variety of reasons why such schemes may not improve outcomes after students enroll in college. First, improvements in outcomes may reflect test-taking effort so that the contemporaneous gains in test scores may not persist.[9] Second, marginal

I find that affected students took and passed more AP exams, and enrolled in college in greater numbers – consistent with Jackson (2010). Moreover, conditional on college enrollment, affected students had higher grades and increased persistence. Improvements were relatively larger for black and Hispanic students and I find suggestive evidence that affected black and Hispanic students were more likely to graduate with a four-year degree. I show that these graduation results are unlikely to reflect faster time to degree. While the short-run outcomes were similar across schools (as in Jackson 2010), the long-run college effects were largest in schools with established AP programs before APIP adoption (and had little AP course expansion) and schools with high-powered incentives – suggesting that increased supply of AP courses was not the driving mechanism, and that increased teacher and student effort are important aspects of the program's success. Also, the program effects grow over time, indicating that the non-incentive aspects of the APIP are important. Guidance counselors credit increased AP participation to increased encouragement from teachers, better student information, and changes in teacher and peer norms – consistent with the APIP reducing suboptimal decisions.

These findings indicate that both maintaining high standards, and increasing participation in rigorous high-school programs can improve college readiness. The results suggest that incentive programs that include resources to turn increased effort into achievement may have lasting positive effects even after rewards are no longer provided. These findings also contribute to the debate on early versus late interventions as they show that an inexpensive program targeted to high-school students is effective at increasing educational attainment.

The remainder of this paper is structured as follows. Section II describes the APIP program. Section III presents the theoretical framework. Section IV presents the data. Section V discusses the empirical strategy. Section VI presents the results, specification and robustness tests, shows that the results cannot be driven by changes in out-of-state college going, and presents evidence on mechanisms. Section VII concludes.

II. Description of the AP incentive program

AP courses are common in US high schools and are typically taken by students in 11th and 12th grade. The courses are intended to be "college level" and most colleges allow successful AP exam takers to use them to offset degree requirements.[11] The fact that selective colleges pay

[11] While this is true in general, some highly selective colleges only allow students to use AP credits to pass out of

attention to a student's AP scores in the admissions process demonstrates that the exams are considered to be revealing about a student's likely preparation for and achievement in college. The AP program has 35 courses and examinations across 20 subject areas. The length of a course varies from one to two semesters. The cost per examination is $82 and a fee reduction of $22 is granted to those students with demonstrated financial need. AP exams are administered by the College Board, making teacher cheating unlikely. Exams are graded from 1 through 5, where 3 and higher are regarded as passing grades. AP courses are taught during regular class time and generally substitute for another course in the same subject (AP Chemistry instead of 11th grade science for example), for another elective course, or a free period. While AP courses count towards a student's high school GPA, they are above and beyond what is required for high school graduation. As a rule, AP courses substitute for less demanding activities.[12]

The APIP is run by AP Strategies, a non-profit organization based in Dallas, and is entirely voluntary for schools, teachers, and students. The heart of the program is a set of financial incentives for teachers and students based on AP examination performance. It also includes teacher training conducted by the College Board and a curriculum that prepares students for AP courses in earlier grades. The APIP uses "vertical teams" of teachers. At the top of a vertical team is a lead teacher who teaches students and trains other AP teachers.[13] Vertical teams also include teachers whose grades precede those in which AP courses are offered. For example, a vertical team might create a math curriculum starting in 7th grade designed to prepare students for AP calculus in 12th grade. In addition to the AP courses taught at school, there may be extra time dedicated to AP training. For example, the APIP in Dallas includes special "prep sessions" for students once or twice a year, when up to 800 students gather at a single high school to take seminars from AP teachers as they prepare for their AP exams (Hudgins 2003).

The APIP's monetary incentives are intended to encourage participation and induce effort in AP courses. AP teachers receive between $100 and $500 for each AP score of 3 or over earned by an 11th or 12th grader enrolled in their course and can receive discretionary bonuses of up to $1,000 based on results. In addition, lead teachers receive between $3,000 and $10,000 annual salary bonus, and a further $2,000 to $5,000 bonus opportunity based on results. While the amount paid per passing AP score and the salary supplements are well defined in each

---

prerequisites, but not towards regular graduation credit.

[12] Source: Executive Vice President AP Strategies and counselors at several Dallas high-schools.

[13] Jackson and Bruegmann (2009) find that teachers learn from their peers so that vertical teams may be effective.

school, there is variation across schools in the amounts paid. Overall, the APIP can deliver a considerable increase in compensation for teachers.[14]

Students in 11th and 12th grade also receive monetary incentives for performance. The program pays half of each student's examination fees so that students on free or reduced lunch would pay $15 (instead of $30) while those who are not would pay $30 (instead of $60) per exam. Students receive between $100 and $500 for each score of 3 or above in an eligible subject for which they took the course. The amount paid per exam is well defined in each school, but there is variation across schools in the amount paid per passing AP exam. A student who passes several AP examinations during their 11th and 12th grades can earn several hundred dollars. For example, one student earned $700 in his junior and senior years for passing scores in AP examinations (Mathews 2004). Since students must attend the AP courses and pass the AP exams to receive the rewards, students who did not take the AP courses would not take the exams in an attempt to earn the cash rewards. This aspect of the incentives makes them relatively difficult to game and likely to increase overall student learning.

The total cost of the program ranges from $100,000 to $200,000 per school per year, depending on the size of the school and its students' propensity to take AP courses. The average cost per student in an AP class ranges from $100 to $300. Private donors pay for between 60 and 75 percent of the total costs, and the district covers the remainder. Districts pay for teacher training and corresponding travel, release time and some of the supplies and equipment costs. Donors fund the cash rewards to students and teachers, stipends to teachers for attending team meetings, bonuses to teachers and administrators for AP performance, and some of the supplies and equipment costs. Today, districts can fund their contribution to the APIP using earmarked funds from the statewide AP incentive program and No Child Left Behind. However, in the first few years of the program such funds were not available.

As a rule, adoption of the APIP works as follows. First, interested schools approach AP Strategies and are put on a list.[15] AP Strategies then tries to match interested schools to a donor. When a private donor approaches AP Strategies, he or she selects which schools to fund from

[14] One AP English teacher in Dallas had 6 students out of 11 score a 3 or higher on the AP examination in 1995, the year before the APIP was adopted. In 2003, when 49 of her 110 students received a 3 or higher, she earned $11,550 for participating in the program; this was a substantial increase in annual earnings (Mathews 2004).

[15] There are a few exceptions. Schools in Austin were approached by the donor to adopt the APIP in 2007. Also, five schools in Dallas secured a donor before approaching AP strategies.

within the group of willing sc

TUVEFOU FGGPSU FDPOPNJD BHFOUT JO UIJT DBTF UFBDIFST BOE TUVEFOUT XJMMFYFSU NPSF FGGPSUUP

FIpDMFT P" &@XO SFBT

JNQSPWF TVDI PVUQVU)PMNTUSPN BOE . JMHSPN 5IFSFGPSF POF XPVME FYQFDU " JODSFBTFT

JOUFBDIFS SFDSVJUNFOUFGFYQFOUY

admitted to college conditional on applying. While the APIP should increase the college going of college applicants, the total effect on college going is ambiguous in sign.

summary statistics from the National Center for Education Statistics and the Texas Education Agency (TEA) in Table 1. Schools that were selected for the APIP were different from schools that have not been selected and may never be selected for the APIP. The APIP schools had average enrollments during 2000 through 2005 of 1836 students compared to 751 students for non-APIP schools in Texas. During these years, 74 percent of the APIP schools were in a large or mid-sized city compared to under 20 percent for non-APIP schools. During these years, only during the pre-adoption years took an AP course while in high school compared to 30.4 percent in the post adoption period. There were similar increases in AP examination taking where those in 10th grade during the pre period took 0.097 exams and those in the post period took 0.127 exams during their high school career. The 10th grade math and reading standardized scores were below zero for both periods - indicating that the APIP schools were low achievement schools on average. Also, these scores were slightly lower after adoption than before - suggesting possible negative selection into APIP schools.

The average student before adoption was in 10th grade in 1999 compared to 2003 for the post adoption sample. As such, variables that increase with age such as college attendance and completion are difficult to compare without explicitly taking age into account (as is done the regression analysis). However, to allow for a simple comparison, I compute enrolment by the time since expected high school graduation cohort. About 35, 46, and 53 percent of 10th graders in the pre-treatment cohorts were a freshman in college within 1, 2, and 3 years of expected high school graduation respectively. The 10th graders in post adoption cohorts were more likely to attend college such that 41, 50, and 56 percent of 10th graders in the post-treatment cohorts were a freshman in college within 1, 2 and 3 years of expected high school graduation, respectively.[28] The implied sophomore year persistence (the share of students who were sophomores divided by the share who were freshmen) is 0.53 and 0.544 for the pre- and post-adoption cohorts, respectively.[29] Comparing figures for ever being a freshman to the enrolment figures above reveal that 59, 79, and 89 percent of college going occurs within one, two and three years of expected high-school graduation, respectively. Because analyzing enrolment within four years of expected high-school graduation ignores enrolment that occur after four years (one tenth of the variation), I analyze eventual enrolment and control for cohort differences directly.

V. Empirical Strategy

Before presenting the identification strategy, In section V.1, I discuss methodological concerns facing this and similar studies and I present my proposed solutions. In section V.2, I present the identification strategy and discuss the source of plausibly exogenous variation.

---

[28] Texas has the second largest and well developed community college system in the United States so that a sizable share of these students enroll in 2-year colleges.

[29] The sophomore variables are not computed for the 2007 cohort, because they would be freshman in 2010 if they enrolled directly after expected high-school graduation. Also, college graduation variables are only computed for cohorts before 2004 because subsequent cohorts would not typically have graduated from a 4-year college by 2010.

V.1 Methodological Issues: Because the APIP affects students in 11^{th} and 12^{th} grade, it affects the characteristics of students while still in high school so that one must compare students who were similar *before* exposure to the APIP. As such, I compare the outcomes of students with at APIP schools in 11th and 12th grade to benefit from the program, defining treatment based on actual school enrollment in 11th and 12th grade could be subject to self-selection bias. To avoid such bias, I use intention-to-treat instead of whether a student is actually affected by the APIP. Specifically, I define intention-to-treatment (ITT) based on whether a student would be treated if they remain in their 10th grade high school and are never held back a grade. For example, a student is intended for treatment if they are enrolled at a school in 10th grade in year t and the school will have adopted the APIP by year $t+2$. The benefit of using ITT is that it is not endogenously determined by student selection into APIP schools in 11th and 12th grade, or subject to biases due to attrition or retention.[33] Using ITT yields a clean policy-relevant estimate of the effect of introducing the APIP on the target population.

V.2 Identification Strategy: The identification strategy is to compare the difference in college outcomes across cohorts of students who attended the same high-school before and after APIP adoption to the difference in college outcomes between cohorts of students at schools that did not adopt the APIP over the same time period. Comparing students from the same high school addresses the concern that students at schools that adopt the APIP may differ from students who attend schools that do not adopt the APIP. By comparing cohorts, as opposed to students within cohorts, I address the concern that certain types of students tend to take AP courses and exams for unobserved reasons while others do not. Furthermore, by comparing the college outcomes of students with the same 10th grade test scores and demographics, I address the concern that the incoming preparation of students may have changed in APIP schools after adoption of the program. Finally, this approach helps to account for potentially confounding statewide policies.[34]

This strategy relies on the assumption that the difference in outcomes across cohorts for comparison schools is the same, in expectation, as the difference in outcomes across cohorts that adopting schools would have experienced if they had not adopted the APIP. For this to be plausible, the comparison schools must be similar to APIP adopting schools. To ensure that this is the case, I restrict the estimation sample to those schools that had adopted the APIP by 2008 – using the change in outcomes for other APIP schools that did not yet have the opportunity to implement the program as the counterfactual change in outcomes. This sample restriction has

[33] The downside of this measure is that it will not capture the full effect of the treatment on the treated

two important benefits: (1) because APIP willing schools are observationally similar, they likely share common time shocks and (2) because APIP willing schools are similarly motivated and interested, restricting the sample in this way avoids comparing schools with motivated principals to schools with unmotivated principals who have no interest in the program.[35]

Because I do not compare schools that adopt the intention to treat year. Standard errors are adjusted for clustering at the school level.

It is important to point out that a simple before/after comparison likely understates the

statistically insignificant increases in college selectivity among college goers (not shown).[37]

Because the outcomes analyzed are using Texas college data, it is important to ensure that increased college enrolment does not reflect shifting of college going from out-of-state to in-state. I test this directly using data from the National Student Clearinghouse (NSC) for the 10th grade cohorts of 2005 and 2006. These data measure college enrollment both at in-state and out-of-state colleges and universities. Because I only have NSC data for two cohorts, I can only estimate effects for the first and second ITT cohorts. The results in columns 7 and 8 show that by the second ITT year the APIP increases in-state college going by 3.5 percentage points (significant at the 5 percent level) but has no effect on out-of-state college going (a point estimate of -0.0001 that is not close to statistical significance in the second ITT year). These results are similar to those obtained using the THECB data (for all years and also for these two cohorts) thus validating the college going numbers from the THECB data and showing that the enrollment effects measured in this study reflect real increases in college going and are not confounded with changes in out-of state college going.

IV.3 Effects on Freshman GPA. In columns 1 through 3 of table 4, I present the effect on Freshman year GPA conditional on college enrollment. In models of college enrollees that include the estimated propensity scores to account for selection to college (column 3), treated cohorts had freshman year GPAs that were 0.03 points higher (significant at the 10 percent level). This GPA effect increases over time so that GPAs were 0.067 points higher in the fourth treated cohort than in untreated cohorts (significant at the 5 percent level). Using all students and imputing GPAs for non-enrollees (based on observable characteristics) yields a before/after effect of 0.015 points (significant at the 5 percent level), and a fourth year effect of 0.031 grade points (significant at the 1 percent level). I also implemented a trimming procedure to obtain a lower bound effect. However, the lower-bound effect is large negative, and therefore uninformative and not presented in the table. To shed further light on how much of the APIP effect is driven by the extensive margin (college entry) as opposed to the intensive margin (GPA conditional on enrolling in college), in Figure 3, I present the coefficient on the simple post adoption indicator variable using the full sample under different imputed GPA values for those who do not attend college. If one assumes students who do not enroll in college would have

---

[37] I linked the college identifiers for college enrollees to the mean SAT scores of admitted students from IPEDS. Treated cohort attended colleges with slightly higher SAT scores. The increase in the 25th percentile of combined math and reading SAT scores was 32 points (not statistically significant).

received a GPAs of 0, 1, and 2 (an F, D, and C average, respectively) then the before/after effects would be 0.048, 0.034, and 0.021 grade points, respectively. If one makes the unrealistic assumption that non-enrollees would have had the same GPA as those who did enroll (2.3 about a C+ average) the adoption effect would be 0.017 grade points (significant at the 5 percent level). In fact, the 95 percent confidence interval of the estimated APIP effect to includes zero for all assumed values below 2.7 (a B- average), the point estimates are positive until an assumed GPA of 3.6 (an A- average), and is essentially zero (0.006) if one assumes that non-enrollees would have had a 4.0 (straight As). Figure 3 shows that under reasonable assumptions of what the GPAs would have been for non-enrollees, APIP exposure is associated with improved freshman year GPAs conditional on college enrollment.

To provide a sense of where in the achievement distribution these improvements in freshman GPA might come from, Figure 4 presents cumulative densities of the freshman GPA of treated and untreated cohorts. It is evident that there are slight improvements in GPA for treated cohorts below the 40th percentile (GPA between 0 and 2), but that the 40th through 90th percentiles are clearly higher in the treated group (corresponding to GPAs between 2 and 4). This suggests that much of the improved GPAs came from student between the 40th and 90th percentile of the achievement distribution in college who would have had averages between a C and an A- without the APIP.

IV.4 Effect on sophomore year enrollment and persistence: Most college attrition occurs in the first year so that persistence through the first year is a key predictor of college success. In Table 4 I present the effect on being a college sophomore and persisting to sophomore year (enrolled as a college sophomore conditional on ever being a college freshman). Column 4 shows the results for the full sample, and columns 5,6,7 and 8 show the results conditional on college enrollment with no sample selection co treated sample for a lower-bound effect yield a statistically insignificant pooled effect of 1 percentage point, but a 6.6 percentage point increase by year four (significant at the 5 percent level). These results show real increases in sophomore year attendance, due, in large part, to increased persistence for those who would have enrolled in college absent the APIP.

Another way to obtain a lower-bound persistence effect is to make the extreme assumption that all the marginal freshman enrollees would persist to sophomore year (Dynarski 2008). The average persistence rate is 0.52 so this is unlikely. The fourth year freshman and sophomore enrollment effects are 4.8 and 6 percentage points, respectively. If all the marginal enrollees would have persisted, this leaves 6-4.8 = 1.2 percentage points that must be due to the non-marginal students. As such, even under the lower-bound assumption, the APIP increases college persistence conditional on college enrolment by at least 2.3 percent by year four. A more realistic, but still conservative, assumption is that the marginal student would persist at the same rate as the average student. Under this assumption 4.8*0.52= 2.5 percent may be due to marginal enrollees, so that 6-2.5=3.5 percentage points is due to the inframarginal students (yielding a 6.7 percent increase in sophomore year persistence conditional on enrolling).

Timing of the Enrollment effect: Readers may wonder if these enrollment effect merely reflect that the APIP causes students to enroll in school sooner. To assess this, I analyze enrollment within 1,2,3 and 4 years of expected high school graduation in Table 5. If the effects were due to students enrolling in school sooner rather than later, one would see stronger effects on enrollment close to high school graduation and no effect within longer time horizons. For example, if students attended college within one year of high-school graduation rather than two or three, one would see effects on "ever a freshman within 1 year of high-school graduation" but would see no effect on "ever a freshman within 4 years of high-school graduation". The effects on freshman enrollment and sophomore enrollment grow as one looks to longer time horizons, which is exactly what one would see if the effect reflects increased college going overall, and is inconsistent with the results being due to shifting to earlier college entry. This also indicates that much of the increased college going occurs after four years after expected high school graduation, so that analyzing short run college going would miss an important part of the story.

VI.5 Threats to Validity and Endogeneity Concerns: While I am careful to compare cohorts within the same school to avoid self-selection within a cohort and selection across schools, and I limit the estimation sample to only the APIP schools that are of similar motivation, there are a few remaining endogeneity concerns regarding whether the estimates reflect a true causal relationship. I address these in this section.

The timing of APIP adoption may be endogenous. There is the concern that schools that had an increase in motivation were more likely to apply to have the APIP implemented. The APIP takes about two full years to be implemented after a school expresses interest. As such, if the results merely reflected changes in school motivation that coincided with expressing interest in the APIP, one should see an improvement in outcomes two years prior to adoption. There is no visually evidence of this and I fail to reject the null hypothesis of improvements in outcomes before adoption. As a direct test of the "timing-interest" hypothesis, I regressed the outcomes on the two-year lag of adoption. This yielded very small coefficient estimates and p-values larger than 0.4 for all outcomes.

To provide further evidence that the timing of APIP adoption is exogenous, I predict having a new high school principal as a function of whether program will be adopted in 3 years, 2 years, 1 year, or was adopted in the same year. These models include school fixed effects and year fixed effects only. In each of these 4 regressions (shown in appendix Table 4) the p-values associated with the null hypothesis of no systematic relationship is larger than 0.2. I also estimate a specification similar to equation (1) and find no effect on subsequent principal turnover (Appendix Table 6). This is consistent with assertions that timing of adoption is idiosyncratic, and suggests that adoption is likely exogenous to changes in schools over time.

High-ability, motivated students may self-select into APIP schools after adoption. Another concern is that these improvements are the result of motivated students self-selecting into secondary schools that adopt the APIP.[38] If there were positive selection driving the results, the APIP should be associated with characteristics associated with better outcomes. To test for this I predict the main outcomes as a function of observable student characteristics before APIP

38

adoption. I then regress the predicted outcome the benefits to the APIP are driven by improvements in or increased effort in the AP program, or due to other school-wide changes (such as better inputs, or change in teaching philosophy) that might have been affected by APIP adoption. If improved outcomes are driven by improved AP instruction, increased AP participation, or both, one should see large effects for students who take AP courses and little effect for students who do not. I test this by comparing the effect of the APIP on students who are ex-ante (based on pre-adoption characteristics) likely and unlikely to take AP courses (Figure 5).[40] While one cannot reject the null hypothesis of no adoption effect for those with estimated likelihood below 0.33 at the 10 percent level, there are large statistically significant APIP effects for students with estimated likelihood above 0.66. This suggests that (a) the benefits of the APIP are experienced by AP students and (b) the estimated effects are not driven by other confounding changes at schools.

As an additional test, I look at the APIP effectw 8.655 and (b) theo338al test,rTT1inpud 20.01l, null hypothesis that there are gender differences in response at the 10 percent level. Specifically, females have a smaller increase in AP courses taken and about a 50 percent larger increase in overall college going by the fourth APIP year. For all outcomes conditional of college entry, the result are similar for males and females, such that while females were more likely to enroll in college due to the APIP, the effect on their college outcomes are similar.

#FGPSF BOBMZ[JOH EJGGFSFODFT CZ FUIOJDJUZ * QSFTFOU TVNNBSZ TUBUJTUJDT JO 5BCMF GPS XIJUF CMBDL BOE)JTQBOJD TUVEFOUT "CPVU QFSDFOU PG CMBDL UI HSBEFST JO UIF TBNQMF UBLF BOZ "1 DPVSTF POMZ QFSDFOU UBLF BOZ "1 FYBNT BOE UIF BWFSBHF OVNCFS PG FYBNT QBTTFE JT

4JNJMBS UP CMBDL TUVEFOUT BCPVU QFSDFOU PG)JTQBOJD UI HSBEFST JO UIF TBNQMF UBLF BOZ "1 DPVSTF POMZ QFSDFOU UBLF BOZ "1 FYBNT BOE UIF BWFSBHF OVNCFS PG FYBNT QBTTFE JT

*O DPOUSBTU BCPVU QFSDFOU PG XIJUF UI HSBEFST UBLF BOZ "1 DPVSTF QFSDFOU UBLF BOZ "1 FYBNT BOE UIF BWFSBHF OVNCFS PG FYBNT QBTTFE JT /PU TVSQSJTJOHMZ UIFTF EJGGFSFODFT JO "1 PVUDPNFT BSF BTTPDJBUFE XJUI EJGGFSFODFT JO DPMMFHF PVUDPNFT 5IF DPMMFHF HPJOH SBUFT GPS CMBDLT)JTQBOJDT BOE XIJUFT BSF BOE QFSDFOU SFTQFDUJWFMZ &WFO DPOEJUJPOBM PO FOSPMMJOH UIFSF BSF EJGGFSFODFT TP UIF GSFTI NBO ZFBS (1" T GPS CMBDLT)JTQBOJDT BOE XIJUFT XFSF BOE SFTQFDUJWFMZ *U JT XPSUI OPUJOH UIBU TPNF PG UIFTF EJGGFSFODFT NBZ SFGMFDU EJGGFSFODFT JO QSFQBSBUJPO BT CMBDL BOE)JTQBOJD UI HSBEFST IBE NBUI BOE SFBEJOH UFTU TDPSFT CFUXFFO BOE TUBOEBSE EFWJBUJPOT MPXFS UIBO XIJUFT PO BWFSBHF

5IF SFTVMUT JO 5BCMF SFWFBM EJGGFSFODFT BDSPTT FUIOJD HSPVQT 8IJMF UIFSF BSF TNBMM EJGGFSFODFT JO "1 DPVSTF UBLJOH BOE "1 FYBN UBLJOH POF SFKFDUT UIBU UIF "1*1 SFTQPOTF JT UIF TBNF CFUXFFO XIJUF CMBDL BOE)JTQBOJD TUVEFOUT BU UIF QFSDFOU MFWFM GPS DPMMFHF HPJOH (1" BOE QFSTJTUFODF UP TPQIPNPSF ZFBS (JWFO UIF MBSHF EJGGFSFODFT JO CBTFMJOF "1 PVUDPNFT UIF JODSFBTFT JO "1 FYBN UBLJOH SFQSFTFOU B OFBS EPVCMJOH

5IF EJGGFSFODFT JO DPMMFHF PVUDPNFT BDSPTT FUIOJD HSPVQT SFWFBM TPNF JOUFSFTUJOH QBUUFSOT 8IJMF CMBDL BOE XIJUF TUVEFOUT FYQFSJFODF JODSFBTFT JO DPMMFHF HPJOH UIFSF JT OP JODSFBTF JO DPMMFHF HPJOH GPS)JTQBOJDT -PPLJOH UP (1" DPOEJUJPOBM PO FOSPMMJOH XIJMF XIJUF TUVEFOUT IBWF MJUUMF SFTQPOTF JO UIJT PVUDPNF CZ UIF GPVSUI "1*1 ZFBS CMBDL TUVEFOUT IBWF GSFTI NBO ZFBS (1"T UIBU BSF CFUXFFO BOE IJHIFS UIBO UIPTF OPU FYQPTFE UIFTF FGGFDUT BSF TJHOJGJDBOU BU UIF QFSDFOU MFWFM 8IJMF OPU TUBUJTUJDBMMZ TJHOJGJDBOU UIF QPJOU FTUJNBUFT TVHHFTU UIBU)JTQBOJD TUVEFOUT NBZ BMTP IBWF IJHIFS (1"T VOEFS UIF "1*1 "MM HSPVQT IBWF JNQSPWFE TPQIPNPSF ZFBS FOSPMMNFOU BOE QFSTJTUFODF DPOEJUJPOBM PO FOSPMMNFOU BOE UIF JNQSPWFNFOUT BSF QBSUJDVMBSMZ QSPOPVODFE GPS CMBDL TUVEFOUT *O NPEFMT UIBU VTF UIF QSPQFOTJUZ TDPSF DPSSFDUJPO CZ UIF GPVSUI "1*1 DPIPSU TPQIPNPSF ZFBS QFSTJTUFODF JODSFBTFT CZ QFSDFOUBHF QPJOUT GPS XIJUFT QPJOUT GPS)JTQBOJDT BOE QPJOUT GPS CMBDLT UIFTF EJGGFSFODFT BSF TUBUJTUJDBMMZ TJHOJGJDBOU BU UIF QFSDFOU MFWFM)PXFWFS JO NPEFMT UIBU VTF JNQVUBUJPO UP BDDPVOU GPS TBNQMF TFMFDUJPO CJBT CZ UIF GPVSUI "1*1 DPIPSU TPQIPNPSF ZFBS QFSTJTUFODF JODSFBTFT CZ QFSDFOUBHF QPJOUT GPS XIJUFT BOE)JTQBOJDT BOE J QPJOUT GPS FBDI

QUJT

college graduation for the students who were in 10th grade before 2003. These students are old enough to have graduated from a 4-year college by 2010. An implication of this data truncation problem is that I may confound reduced time to degree with increased college completion. However, I present evidence that this is likely not the case so that this truncation bias is likely to attenuate the estimates and understate the effects of the APIP on graduation.

Columns 1 and 2 of Table 9 presents the main specification where the outcomes are graduating with any degree, graduating with a degree within 4 years, and graduating with a bachelors (BA) degree. I present results for all students in the top panel, and also black, Hispanic, and white, separately in the lower panels. The results in the top panel show that the APIP has no effect on the graduation variables, on average. However, the results broken up by ethnicity reveal that while there are no graduation effects for whites, treated black and Hispanic students were more likely to earn a bachelors degree (one can reject the null hypothesis of no adoption effect at the 5 percent level for both groups). For black students, the first and third APIP cohorts are 1.8 percentage points more likely to earn a BA degree than those who were not exposed to the APIP, while the effect for Hispanic students increases monotonically with program age. By the fourth year of the APIP Hispanic students are 2.5 percentage points more likely to earn a BA degree. These increases represent a 20 and 31 percent increase for black and

Again, there are larger positive effects on total credits earned than on credits earned within four years of expected high school graduation. Further evidence that the effects are due to increased schooling rather than reduced time to degree. As a final check, I look at junior year enrollment and junior year enrollment within four years of expected high school graduation. The pattern is the same; all groups have modest increases in junior year enrollment within four years and larger effects on ever enrolling as a junior. Further evidence that the effect are due to increased schooling rather than reduced time to degree. To assuage any lingering concerns that these findings are due to differential trends by ethnicity, I estimated models with school-specific trends by ethnicity and the results are qualitatively similar.[42]

courses are no longer considered only for the very brightest of students.

The tests above suggest that increased supply of courses was not the driving force behind the AP participation response or the improvements in college. The fact that the effects are larger in the high incentive schools, suggests that providing additional supply and removing barriers to taking AP courses alone would not lead to success, who were ex ante likely to take AP courses. The evidence on mechanisms indicate that both the incentive aspects and the non-incentive aspects are important. The finding that the program confers enduring benefits on students when extrinsic motivators are no longer provided is important for the literature on student and teacher incentives in light of concerns that incentive-based-interventions may lead to undesirable practices such as "teaching-to-the-test" and cheating. More generally, the lack of any documented ill-effects of the APIP, suggests that many of the hypothesized detrimental effects of using student incentives or teacher performance pay need not pose a large practical problem in a well designed incentive-based scheme that combines incentives with additional recourses to help translate increased effort into results.

To get a sense of the cost-effectiveness of APIP, consider the following conservative back-of-the-envelope cost/benefit calculation. The program costs about $200 per student who takes an AP exam per year. Roughly 7 percent of 10th graders take an AP exam after APIP costs a87 Assucentiv

Overall, the findings suggest that providing monetary incentives to both students and teachers to promote increased participation and improved performance in rigorous courses in addition to providing additional resources to support the increased efforts can lead to meaningfully improved student outcomes. The fact that the positive effects were larger for ethnic minority students suggests that similar programs may help reduce some of the educational differentials that currently exists across ethnic and socioeconomic groups. In light of research on the efficacy of early versus late interventions, these findings are noteworthy because they suggest that a relatively inexpensive program targeted relatively late in a student's educational career can increase their eventual educational attainment to a considerable degree and likely has a high rate of return.

Bibliography

Adelman, C. Answers in the Tool Box: Academic Intensity, Attendance Patterns, and Bachelor's Degree Attainment. Washington, DC: U.S. Department of Education, 1999.

Angrist, Joshua. "Conditioning on the Probability of Selection to Control Selection Bias." NBER Technical Working Paper 181, 1995.

Angrist, Joshua, and Victor Lavy. "The Effects of High Stakes High School Achievement Awards: Evidence from a Group-Randomized Trial." American Economic Review, forthcoming.

Angrist, Joshua, Daniel Lang, and Philip Oreopoulos. "Incentives and Services for College Achievement: Evidence from a Randomized Trial." American Economic Journal: Applied Economics, 1:1 (2009): 136-163.

Angrist, Joshua, Eric Bettinger, and Micheal Kremer. "Long-Term Consequences of Secondary School Vouchers: Evidence from Administrative Records in Colombia." Amercian Economic Review, June 2006.

Belley, Philippe, and Lance Lochner. "The Changing Role of Family Income and Ability in Determining Educational Achievement." Journal of Human Capital, 1, no. 1 (2007): 37-89.

Berry, James. "Child Control in Education Decisions: An Evaluation of Targeted Incentives to Learn in India." unpublished mimeo Cornell University, 2009.

Bettinger, Eric P. "Paying to Learn: The Effect of Financial Incentives on Elementary Test Scores." unpublished, 2009.

Bettinger, Eric P., Bridget Terry Long, Philip Oreopoulos, and Lisa Sanbonmatsu. "The Role of Simplification and Information in College Decisions: Results from the H&R Block FAFSA Experiment." NBER Working Paper 15361, 2009.

Bowen, William, and Derek Bok. The shape of the river: Long-term consequences of considering race in college and university admissions. Princeton, NJ: Princeton University Press, 1998.

Bradburn, Ellen M. Short-term Enrollment in Postsecondary Education: Student Background and Institutional Differences in Reasons for Early Departure. Washington, D.C.: U.S. Department of Education National Center for Education Statistics, 2002.

Braun, Henry, and Irwin Kirsch. "Testing the Effect of Incentives on

Hispanics." Journal of Political Economy, 2001.

Costrell, Robert M. "An Economic Analysis of College Admission Standards." Education Economics 1, no. 3 (1993): 227-241.

Cunha, Flavio, and James Heckman. "The Technology of Skill Formation." American Economic Review 97, no. 2 (2007): 31-47.

Cunha, Flavio, James J. Heckman, and Lance, Lochner. Interpreting the Evidence on Life Cycle Skill Formation. Elsevier, 2006.

Currie, Janet. "Early Childhood Education Programs." Journal of Economic Perspectives 15, no. 2 (2001): 213-238.

Deci, Edward. L., and Richard. M. Ryan. Intrinsic Motivation and Self-Determination in Human Behavior. New York: Plenum, 1985.

Deming. "Early Childhood Intervention and Life-Cycle Skill Development: Evidence from Head Start." American Economic Journal: Applied Economics 1, no. 3 (2009): 111-134.

Dougherty, Chrys, Lynn Mellor, and Shuling Jian. The Relationship between Advanced Placement and College Graduation. AP Study Series Report 1, February, National Centre for Education Assessment, 2006.

Dynarski, Susan. "Building the Stock of College-Educated Labor." Journal of Human Resources 43, no. 3 (2008): 676-610.

Eimers, Mardy. "Dual Credit and Advanced Placement: Do They Help Prepare Students for Success in College?" MidAIR and AIR Conference. Tampa, Florida, 2003.

Figlio, David N., and Joshua Winicki. "Food For Thought: The Effects Of School Acco

Klopfenstein, K. "The advanced placement expansion of the 1990s: How did traditionally underserved students fare?" Education Policy Analysis Archives 12, no. 68 (2004).
Kohn, A. Punished by rewards the trouble with gold stars, incentive plans, A's, praise, and other bribes. Bridgewater, NJ: Replica Books., 1999.
Kremer, Michael, Edward Miguel, Rebecca Thornton, and Owen Ozier. "Incentives to Learn." World Bank Policy Research Working Paper 3546, 2004.
Lavy, Victor. "Performance Pay and Teachers' Effort, Productivity and Grading Ethics." American Economic Review, December 2009.
Lee, David. S. "Trimming for Bounds on Treatment Effects with Missing Outcomes." NBER Technical Working Paper T0277, June 2002.
Lyon, J. "Program to offer students money for high test scores." Arkansas News Bureau, October 9, 2007.
Mathews, J. "Paying Teachers and Students for Good Scores." The Washington Post, August 10, 2004.
Medina, J. "Making Cash a Prize for High Scores on Advanced Placement Tests." The New York Times, October 15, 2007.
Neal, Derek, and William Johnson. "The Role of Premarket Factors in Black-White Wage Differences." The Journal of Political Economy 104, no. 5 (1996): 869-895.
Scott-Clayton, Judith. "On Money and Motivation: A Quasi-Experimental Analysis of Financial Incentives for College Achievement." Unpublished mimeo, 2008.
Seftor, Neil S., Arif Mamun, and Allen Schirm. "The Impacts of Regular Upward Bound on Postsecondary Outcomes 7-9 Years After Scheduled High School Graduation." Mathematica Report, 2009.
Stinebrickner, Todd R., and Ralph Stinebrickner. "Learning about Academic Ability and the College Drop-out Decision." NBER Working Paper 14810, 2009.
Summers, Clyde W. "Preferential Admissions: An Unreal Solution to a Real Problem." University of Toledo Law Review 2, no. 2-3 (1970): 377-402.
Tienda, Marta, and Sunny Xinchun Niu. "Flagships, Feeders, and the Texas Top 10% Law: A Test of the "Brain Drain" Hypothesis." The Journal of Higher Education 77, no. 4 (2006).
Tinto, V. Leaving College: Rethinking the Causes and Cures of Student Attrition. Second Edition. Chicago: University of Chicago Press, 1993.

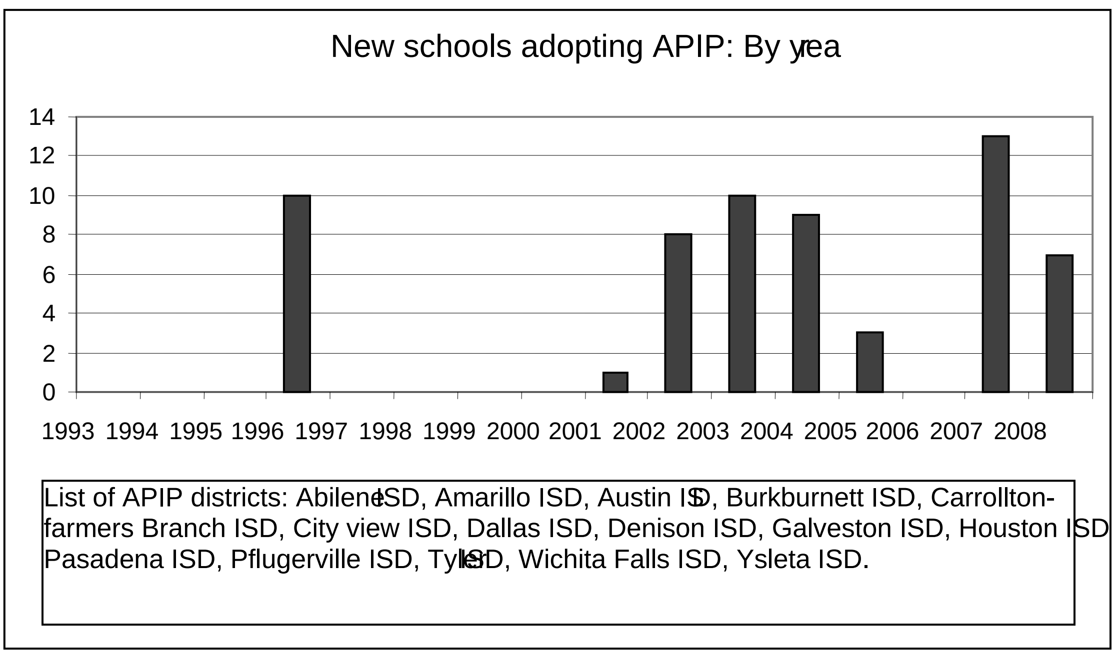


Figure 1: New APIP schools by year.

Note: For all outcomes, the F-statistic associated with the null-hypothesis that the pre-treatment years differ from year t-1 yield p

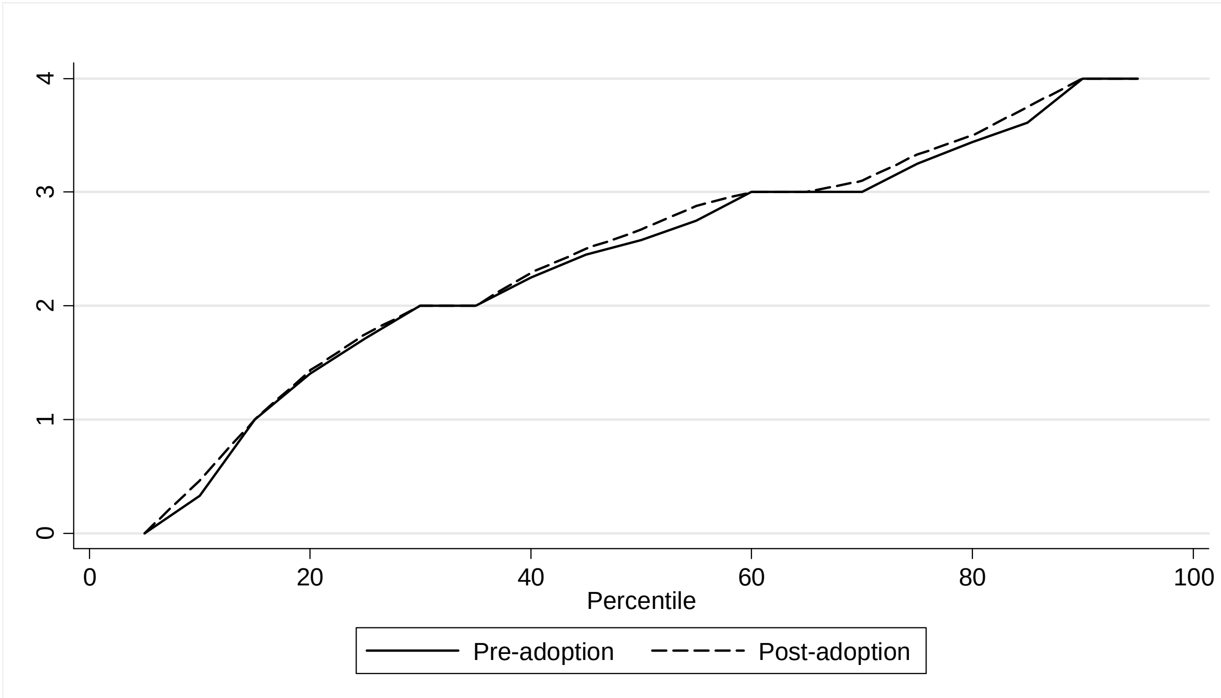


Figure 4: Distribution of GPA in pre- and post-adoption cohorts.

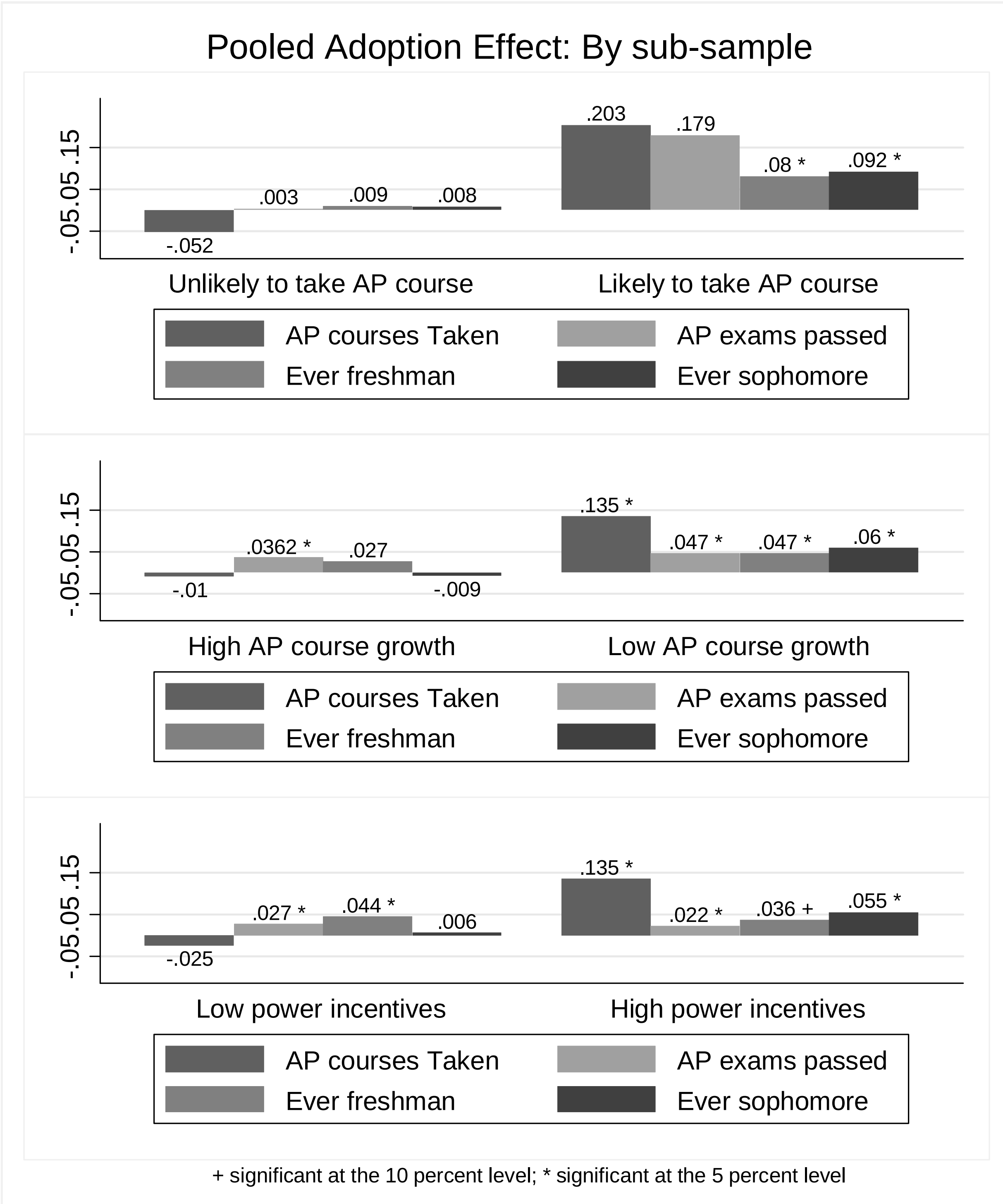


Figure 5: Effect of the APIP on different sub-samples

Table 1

SUMMARY STATISTICS FOR DEMOGRAPHICS FOR APIP SCHOOLS AND OTHER COMPARISON GROUPS

	APIP Schools		Non-APIP Schools	
	1993-1999	2000-2005	1993-1999	2000-2005
Enrollment	1777.68	1836.36	716.85	751.56
	(642.34)	(648.86)	(781.97)	(833.36)
% White	30.82	25.16	59.38	53.36
	(25.43)	(23.28)	(29.46)	(30.42)
% Black	30.17	26.24	10.32	11.30
	(26.82)	(23.5)	(15.64)	(17.08)
% Hispanic	35.76	45.36	28.92	33.67
	(23.49)	(23.84)	(28.9)	(29.5)
% Asian	2.93	2.39	1.09	1.12
	(3.43)	(3.65)	(2.76)	(2.98)
% Free lunch	34.33	41.60	30.42	35.51
	(22.3)	(25.0)	(23.97)	(26.25)
% Limited English	9.66	10.68	3.57	3.83
	(12.89)	(11.86)	(7.71)	(6.8)
City	0.874	0.739	0.182	0.197
	(0.28)	(0.44)	(0.39)	(0.4)
Rural	0.000	0.017	0.489	0.373
	(0.0)	(0.13)	(0.5)	(0.48)
Number of Schools	58		1413	

Table 2

Student Level Summary Statistics of APIP Schools Before and After APIP Adoption

Variable	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.
	Not Adopted APIP			Adopted APIP		
Grade 10 Year	156858	1998.678	(3.247)	137704	2003.117	(3.335)
LEP	156858	0.112	(0.315)	137704	0.138	(0.345)
Low Income	156858	0.384	(0.486)	137704	0.459	(0.498)
Black	156858	0.206	(0.404)	137704	0.270	(0.444)
Hispanic	156858	0.444	(0.497)	137704	0.426	(0.494)
Asian	156858	0.034	(0.182)	137704	0.037	(0.188)
Native American	156858	0.003	(0.059)	137704	0.004	(0.062)
Female	156858	0.502	(0.5)	137704	0.510	(0.5)
10th Grade Reading z-Score	156858	-0.092	(1.018)	137704	-0.063	(0.987)
10th Grade Math z-score	156858	-0.091	(1.004)	137704	-0.078	(0.962)
Take AP Course	156858	0.229	(0.42)	137704	0.304	(0.46)
AP courses Taken	156858	0.652	(1.539)	137704	0.974	(1.947)
Take AP exam	155753	0.055	(0.228)	138535	0.068	(0.252)
AP Exams Taken	155753	0.097	(0.506)	138535	0.127	(0.598)
AP Exams Passed	155753	0.047	(0.342)	138535	0.054	(0.366)
Freshman at any school	156858	0.592	(0.691)	137704	0.570	(0.684)
Sophomore at any school	156858	0.314	(0.561)	115783	0.310	(0.562)
Junior at any school	154840	0.164	(0.375)	95411	0.155	(0.366)
Freshman year GPA	58685	2.382	(1.176)	44425	2.427	(1.192)
Graduate with a BA	147779	0.146	(0.354)	80931	0.115	(0.319)
Graduate with a AA	156858	0.038	(0.191)	115783	0.021	(0.142)
Graduate with a BA within 5	16871	0.019	(0.137)	71513	0.011	(0.104)
Graduate with a AA within 4	9079	0.004	(0.063)	56773	0.002	(0.042)
Attend college outside TX	2018	0.045	(0.208)	42293	0.037	(0.189)
Attend college in TX	2018	0.398	(0.49)	42293	0.421	(0.494)
Ever freshman at Private	44157	0.020	(0.142)	111838	0.041	(0.197)
Ever freshman at Four year	156858	0.174	(0.386)	137704	0.177	(0.391)
Ever freshman at 2yr	156858	0.418	(0.493)	137704	0.392	(0.488)
Freshman within 0 years	156858	0.351	(0.536)	137704	0.411	(0.585)
Freshman within 1 year	156858	0.462	(0.627)	115783	0.504	(0.653)
Freshman within 3 years	147779	0.527	(0.669)	80931	0.561	(0.687)

Table 3

Regression Estimates: Effect of years of AP adoption on AP course taking and College Enrollment

	1	2	3	4	5	6	7	8
	TEA Data			Texas Higher Education Data			National Student Clearinghouse Data	
	AP courses Taken	AP Exams Taken	AP Exams Passed	Ever Freshman	Ever Freshman at 2yr	Ever Freshman at 4yr	Enrolled Out of State	Enrolled In of State
Adopted	0.061	0.0708	0.0246	0.042	0.019	0.023	-0.001	0.021
(ITT year>0)	[0.063]	[0.011]**	[0.009]**	[0.014]**	[0.010]+	[0.008]**	[0.015]	[0.015]
ITT year=1	-0.008	0.066	0.031	0.029	0.013	0.016	-0.0002	0.016
	[0.053]	[0.012]**	[0.008]**	[0.013]*	[0.010]	[0.007]*	[0.0146]	[0.014]
ITT year=2	0.057	0.086	0.042	0.043	0.02	0.023	-0.001	0.035
	[0.063]	[0.015]**	[0.008]**	[0.015]**	[0.011]+	[0.008]**	[0.015]	[0.017]*
ITT year=3	0.165	0.066	0.028	0.066	0.033	0.034	-	-
	[0.080]*	[0.017]**	[0.009]**	[0.018]**	[0.013]*	[0.011]**	-	-
ITT year=4+	0.074	0.098	0.043	0.048	0.02	[illegible]	-	-
	[0.105]	[0.021]**	[0.011]**	[0.020]*	[illegible]	[illegible]	[illegible]	[illegible]

Table 4

Regression Estimates: Effect of years of APIP adoption on Freshman GPA and Enrolling in college as a sophomore

	1	2	3	4	5	6	7	8
	Freshman Year GPA			Ever a Sophomore				
	None	Imputation	Propensity score	Unconditional	Imputation	None	Propensity score	Trim: lower bound
Adopted	0.03	0.015	0.03	0.03	0.026	0.024	0.024	0.01
(ITT year>0)	[0.018]	[0.007]*	[0.017]+	[0.009]**	[0.008]**	[0.016]	[0.016]	[0.017]
ITT year=1	0.009	0.004	0.009	0.008	0.007	0	-0.001	0.001
	[0.020]	[0.007]	[0.020]	[0.009]	[0.007]	[0.015]	[0.015]	[0.016]
ITT year=2	0.043	0.022	0.044	0.027	0.023	0.008	0.008	-0.004
	[0.026]+	[0.010]*	[0.026]+	[0.010]**	[0.009]*	[0.019]	[0.019]	[0.020]
ITT year=3	0.034	0.02	0.035	0.056	0.047	0.045	0.045	0.03
	[0.032]	[0.014]	[0.032]	[0.012]**	[0.011]**	[0.021]*	[0.021]*	[0.022]
ITT year=4+	0.068	0.031	0.067	0.06	0.055	0.086	0.086	0.066
	[0.029]*	[0.011]**	[0.029]*	[0.015]**	[0.012]**	[0.023]**	[0.023]**	[0.024]**[05m [44 Tm [(0.03)(F-tes

Table 5

Regression Estimates: Effect of APIP adoption duration on the timing of Freshman year entry

	1	2	3	4	5	6	7	8	9
	Freshman within					Sophomore within			
	1 year	2 years	3 years	4 years	5 years	2 years	3 years	4 years	5 years
ITT year=1									

Table 6

Regression Estimates: Effect of APIP program on selected student characteristics by adoption cohort

	1	2	3	4	5	6	7	8	9	10	11	12
	Math Score 10th Grade	Read Score 10th Grade	LEP	Low Income	Black	Hispanic	Predicted: AP Courses	Predicted: AP Exams	Predicted: Attend College	Predicted: GPA	Predicted: GPA (enrollees)	Predicted: Sophomore
Adopted	-0.039	-0.013	0.009	-0.039	0.005	-0.025	0.01	-0.004	-0.001	-0.008	-0.013	0.002
ITT year>0	[0.025]	[0.021]	[0.011]	[0.018]*	[0.011]	[0.012]*	[0.032]	[0.040]	[0.006]	[0.010]	[0.012]	[0.007]
ITT year=1	-0.02	0.013	0.009	-0.021	0.003	-0.014	0.002	-0.007	-0.003	-0.011	-0.019	0
	[0.026]	[0.021]	[0.007]	[0.015]	[0.008]	[0.010]	[0.026]	[0.024]	[0.005]	[0.011]	[0.013]	[0.006]
ITT year=2	-0.051	-0.035	0.005	-0.044	0.005	-0.024	0.015	0.004	-0.005	-0.013	-0.013	0.005
	[0.032]+	[0.024]	[0.012]	[0.021]*	[0.011]	[0.013]+	[0.038]	[0.045]	[0.006]	[0.012]	[0.013]	[0.008]
ITT year=3	-0.049	-0.016	0.011	-0.049	0.001	-0.040	0.014	-0.024	-0.005	-0.001	-0.005	0.005
	[0.034]	[0.030]	[0.016]	[0.024]*	[0.015]	[0.017]*	[0.041]	[0.039]	[0.006]	[0.013]	[0.013]	[0.008]
ITT year=4+	-0.050	-0.047	0.017	-0.068	0.012	-0.045	0.018	0.017	-0.007	0.009	0.002	-0.002
	[0.033]	[0.29]	[0.022]	[0.030]*	[0.016]	[0.020]*	[0.048]	[0.052]	[0.007]	[0.014]	[0.017]	[0.010]
		0.07										
School FX	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FX	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	290343	290343	290343	290343	290343	290343	290343	290343	290343	290343	104367	290343
F: no effect	0.29	0.07	0.45	0.22	0.14	0.15	0.98	0.88	0.89	0.46	0.44	0.63

Robust standard erro

Table 7

Summary Means and Standard Deviations for outcomes by Ethnicity

	Black		Hispanic		White	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Take any AP course	0.225	(0.418)	0.211	(0.408)	0.354	(0.478)
AP courses Taken	0.638	(1.521)	0.560	(1.415)	1.186	(2.107)
Take any AP exams	0.034	(0.182)	0.039	(0.193)	0.106	(0.308)
AP Exams Taken	0.052	(0.333)	0.064	(0.393)	0.203	(0.756)
AP Exams Passed	0.009	(0.133)	0.021	(0.192)	0.113	(0.542)
Read score 10th grade	-0.257	(1.044)	-0.203	(0.995)	0.247	(0.903)
Math score 10th grade	-0.343	(0.966)	-0.203	(0.951)	0.261	(0.939)
LEP	0.008	(0.091)	0.258	(0.438)	0.006	(0.08)
Low income	0.476	(0.499)	0.574	(0.494)	0.146	(0.353)
Female	0.521	(0.5)	0.505	(0.5)	0.499	(0.5)
Ever a freshman	0.566	(0.689)	0.445	(0.618)	0.773	(0.722)
Ever a sophomore	0.256	(0.523)	0.230	(0.494)	0.445	(0.625)
Ever a junior	0.119	(0.327)	0.095	(0.296)	0.266	(0.448)
Freshman GPA	2.071	(1.204)	2.319	(1.187)	2.599	(1.131)
Graduate with BA	0.090	(0.286)	0.080	(0.271)	0.232	(0.422)
Graduate with AA	0.019	(0.137)	0.029	(0.167)	0.041	(0.198)
College outside TX	0.050	(0.217)	0.018	(0.134)	0.071	(0.256)
College in TX	0.383	(0.486)	0.383	(0.486)	0.526	(0.499)
Freshman at Private college	0.047	(0.212)	0.013	(0.114)	0.067	(0.251)
Freshman at 4yr College	0.187	(0.4)	0.099	(0.302)	0.269	(0.454)
Observations	69445		128291		83505	

Table 9

Regression Estimates: Effect of Years of APIP adoption on Longer-run College outcomes by Ethnicity

	1	2	3	4	5	6	7	8	9
	Any degree	Any degree within 4 years	BA	Total Credits	Total Credits within 4 years	Ever a Junior	Junior within 4 years	Ever a sophomore	Ever a freshman
	All (224971 observations)								
ITT year= 1	0.005	0.002	0.008	4.395	1.589	0.016	0.012	0.027	0.033
	[0.006]	[0.003]	[0.006]	[1.843]*	[2.022]	[0.006]**	[0.006]+	[0.010]*	[0.017]+
ITT year= 2	0.003	0	0.008	6.626	2.606	0.019	0.013	0.033	0.053
	[0.009]	[0.004]	[0.009]	[1.708]**	[2.000]	[0.007]**	[0.007]+	[0.010]**	[0.017]**
ITT year= 3	0.005	0	0.009	9.368	5.061	0.022	0.015	0.061	0.065
	[0.012]	[0.004]	[0.012]	[2.205]**	[2.209]*	[0.009]*	[0.009]+	[0.013]**	[0.019]**
ITT year= 4+	-0.018	-0.01	-0.016	4.185	3.708	0.013	0.008	0.065	0.04
	[0.016]	[0.006]+	[0.016]	[2.413]+	[2.457]	[0.011]	[0.010]	[0.016]**	[0.023]+
	Black (54059 observations)								
ITT year= 1	0.016	0.002	0.018	3.131	0.055	0.016	0.013	0.011	0.001
	[0.010]	[0.005]	[0.009]*	[2.819]	[2.190]	[0.009]+	[0.008]+	[0.014]	[0.026]
ITT year= 2	0.01	-0.003	0.011	3.461	-0.775	0.011	0.004	0.011	0.013
	[0.011]	[0.005]	[0.011]	[2.247]	[1.595]	[0.008]	[0.006]	[0.013]	[0.022]
ITT year= 3	0.017	-0.005	0.018	7.68	3.525	0.017	0.012	0.034	0.038
	[0.012]	[0.005]	[0.011]+	[2.600]**	[1.765]+	[0.010]+	[0.008]	[0.014]*	[0.021]+
ITT year= 4+	0.003	-0.01	0.010	5.997	2.94	0.012	0.01	0.047	-0.012
	[0.012]	[0.007]	[0.011]	[3.674]	[1.761]	[0.012]	[0.010]	[0.020]*	[0.025]
	Hispanic (93171)								
ITT year= 1	0.011	0	0.012	1.68	-1.998	0.013	0.004	0.021	0.015

7- ITT4s44.62([0.010])7([0.0055)7( )]TJ /TT1 1 Tf 0.0006 Tc 0 Tw 9.547 -0.02 Td [([0.009]*)[([0.0202.4135 Tw 22.5 0

Appendix

Appendix Table 1: Robustness Checks

Appendix Table 3: Effect on AP exam subjects taken

Effects on log AP exam taking at school in a given year: by subject

	1	2	3	4	5
	Math and Computer Science	English	Social Sciences and History	Science	Art and Music
ITT year= 1	0.084	0.285	0.013	0.134	-0.16
	[0.138]	[0.133*	[0.155]	[0.129]	[0.22]
ITT year= 2	0.082	0.403	0.081	0.028	-0.037
	[0.211]	[0.200]*	[0.261]	[0.176]	[0.365]
ITT year= 3	0.294	0.677	0.244	0.441	0.38
	[0.204]	[0.204]**	[0.305]	[0.213]*	[0.423]
ITT year= 4+	0.214	0.804	0.284	0.803	0.289
	[0.25]	[0.238]**	[0.326]	[0.218]**	[0.328]
Observations	570	570	570	570	570

Heteroskedasticity robust standard errors in brackets are adjusted for clustering at the school level.
* significant at 5% level; ** significant at 1% level. All regressions include school and year fixed effects.

Appendix Table 4: Changes in AP course and exam Takers after Adoption

	1	2	3	4	5	6	7	8	9	10
	AP Exam Takers					AP Course Takers				
	School Rank in 10th Grade Math	School Rank in 10th Grade Reading	Normalized 10th grade Math Score	Normalized 10th grade Reading Score	Predicted GPA	School Rank in 10th Grade Math	School Rank in 10th Grade Reading	Normalized 10th grade Math Score	Normalized 10th grade Reading Score	Predicted GPA
ITT years= 1	-4.436	-1.304	0.013	0.02	0.017	-3.029	0.459	-0.015	0.005	-0.008
	[7.667]	[7.233]	[0.022]	[0.014]	[0.010]	[7.558]	[7.099]	[0.022]	[0.014]	[0.007]
ITT years= 2	-14.888	-6.259	0.012	0.002	0.011	-12.418	-7.98	-0.022	-0.003	-0.007
	[9.446]	[8.397]	[0.043]	[0.022]	[0.015]	[10.529]	[9.328]	[0.043]	[0.024]	[0.012]
ITT years= 3	-10.477	-5.166	-0.056	-0.015	0.001	-4.842	-0.799	-0.07	-0.033	-0.012
	[8.673]	[8.10]	[0.05]	[0.022]	[0.017]	[10.27]	[8.994]	[0.051]	[0.026]	[0.014]
ITT years= 4+	-7.994	-5.513	0.053	0.031	0.029	-1.859	-1.139	-0.002	-0.011	0.008
	[8.64]	[8.773]	[0.058]	[0.028]	[0.019]	[12.805]	[11.867]	[0.058]	[0.031]	[0.016]
School FX	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FX	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	18008	18008	18008	18008	18008	61855	61855	61855	61855	61855

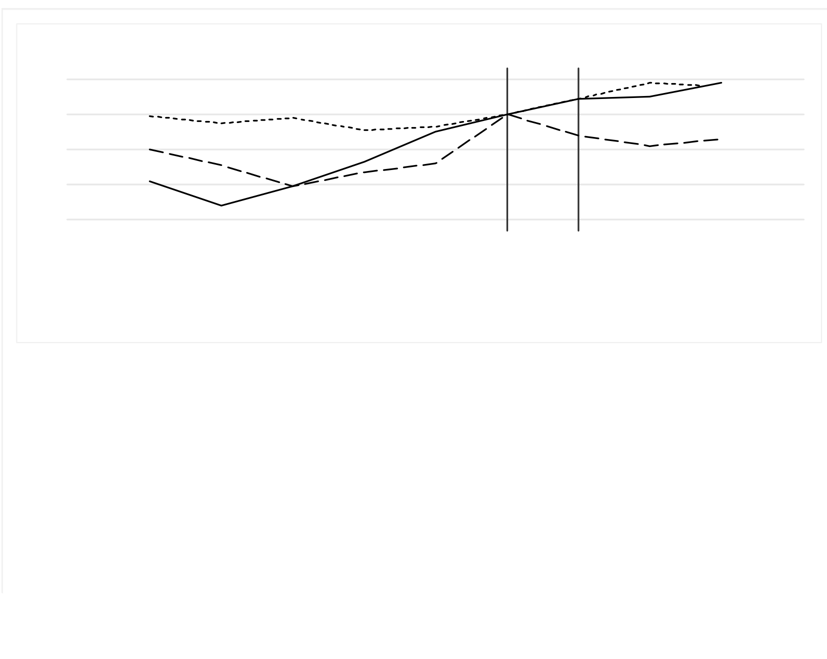
Heteroskedasticity robust standard errors in parenthesis are adjusted for clustering at the school level.
* significant at 5% level; ** significant at 1% level

Dallas schools that started the program in 2003,[45] the donor offered scholarships to any student who was accepted to college. As such, for these schools the APIP effect is potentially confounded with a financial aid effect. To ensure that these 5 schools do not drive the main results, I have replicated the analysis without these five schools and the treatment effects are slightly larger with these school excluded. As such, I can rule out that the few potentially problematic donor relationships bias the results.

Appendix Note 2: Related Statewide Policies During the Sample Period.

The Texas ten percent rule was put in place in 1997 that ensured that the top ten percent of students from each high school in the state would be guaranteed admission to a Texas public university. One would expect college matriculation rates to have increased in schools that have on average low achievement, such as the selected APIP schools, even if these schools did not adopt the APIP. However, none of the APIP schools adopted the APIP in 1997 so that the timing of adoption is not coincident with the introduction of the new state policy. Furthermore, all the main results are robust to using only those schools that adopted the APIP after 2000.

The Texas statewide Advanced Placement Incentive Program was introduced in academic year 1999-2000. Under the statewide program, the state appropriated $21 million over the years 1998-2000 for the Texas APIP, up from $3 million the previous biennium. The statewide program provides a $30 reduction in exam fees for all public school students who are approved to take the AP exams, teacher training grants of up to $450, up to $3,000 in equipment and material grants for AP classes, and financial incentives to the schools of up to $100 for each student who scores 3 or better on any AP exam. One would expect this policy to increase AP participation and effort even if the APIP was not adopted by the selected APIP schools. However all the estimated effects are above and beyond any effect from the statewide program. [Source: Texas Education Agency Press Release: “Number of Advanced Placement Exams Taken by Texas Students Increases Dramatically”. August 23, 2000).



Effect of the APIP on persisting to Junior Year and Graduating by Ethnicity

velt, Sunset, Thomas Jefferson, Seagoville high Schools.