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# How Learning About One's Ability Affects Educational Investments: Evidence from the Advanced Placement Program

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## ABSTRACT

This paper studies how receiving a customized signal of ability affects individuals' educational investments. In 2013, students who took the Preliminary SAT received a message in their results report that signaled their potential to succeed in Advanced Placement (AP) coursework based on their test scores. Survey data from students in the Oakland Unified School District revealed that the signal had informational value, leading students to revise their self-assessed academic ability and plans for AP enrollment, consistent with Bayesian learning. Using a regression discontinuity design, I found that the signal increased the probability of participating in AP classes by 49 percentage points among surveyed students, leading them to enroll in and pass about one more AP course the following year compared to students who did not receive the signal. However, students who were not surveyed for the study did not respond to the signal. The results suggest that ability signals can be a cost-effective way to increase educational investments, but may only work when they are made salient.

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## I. INTRODUCTION

There is substantial mismatch between students' ability and the quality of colleges they attend, which has been traced to students' decisions of where to apply (Hoxby and Avery 2012; Smith et al. 2013; Dillon and Smith 2016). A similar pattern of academic mismatch can be observed even earlier with students' decisions to participate in advanced-level coursework in high school, a key step on the path to a selective college (Geiser and Santelices 2006). Just as behaviors like dropping out of college and changing majors are indicative of incomplete information when these decisions are made (Manski 1989; Altonji 1993), academic mismatch suggests that high school students may lack the necessary information to make optimal decisions about educational investments. One type of uncertainty students may experience is uncertainty about their academic ability and how it compares to other students' abilities.

This paper studies how providing a customized signal of ability affects high school students' beliefs about their ability and decision to take college-level coursework and exams. Students who took the Preliminary SAT (PSAT) in 2013 received a short message at the bottom of their results report that signaled their potential to succeed in Advanced Placement (AP) coursework based on their test scores. Immediately before and after distributing their PSAT results, I surveyed students in a large high school in Oakland, California about their expected performance on the PSAT, their beliefs about their abilities, and their future academic plans. The survey responses enabled me to identify the information shock students experienced as the difference between their prior and posterior beliefs about their PSAT performance. This information shock indicates whether the PSAT report contained any positive or negative surprises for the student.

On average, the PSAT was a negative information shock (that is, students' prior beliefs about their performance tended to be more optimistic than their posterior beliefs after receiving their results report). However, students who received the AP Potential signal experienced more positive shocks, even after holding their PSAT score constant. This result suggests that the AP Potential signal had informational value in addition to that contained in the PSAT score alone. Students who experienced information shocks (good or bad) in turn revised their beliefs about their abilities and academic plans, particularly the number of AP classes they intended to take, in a manner consistent with rational Bayesian updating.

Stated plans may not always reflect future actions. For this reason, I used a regression discontinuity design to estimate whether the AP Potential signal had a causal effect on students' AP course and exam participation. Nonparametric estimates show that receiving the AP Potential signal increased the probability of taking AP courses by 49 percentage points among surveyed students, leading them to enroll in and pass about one more AP course the following academic year compared to students who did not receive the signal. Surveyed students also became more likely to take and pass more AP exams. In addition, being nudged into advanced coursework by the signal had no detrimental effects on these students' academic performance.

When I extended this analysis to students in other Oakland schools who did not take the survey, I found that the AP Potential signal had no effect on their course enrollment or test-taking decisions. This result is not altogether surprising because the signal was not especially conspicuous on PSAT reports, and students and teachers were not aware of its existence. It is also consistent with past studies that show limited responses to individualized messages about eligibility for financial aid and readiness for college (Bettinger et al. 2012; Foote et al. 2015). I interpret this finding as indicative of individuals' inattention to information, which is well-established in the behavioral and macroeconomic literature. Participating in the survey, however, likely raised the salience of the signal. Inattention to information has critical policy implications for the effective distribution of information.

This paper contributes to the literature on learning and expectations formation and joins a growing body of research showing that, in addition to uncertainty about the costs and returns to schooling, beliefs about one's ability also play an important role in educational decisions.[1] According to Goodman (2013), a mandate that made the ACT compulsory for high school juniors led to increased enrollment of students from lower socioeconomic backgrounds in more selective colleges, potentially by showing students who otherwise would not have taken the ACT that they had higher ability than they believed. Jacob and Wilder (2010) found that disadvantaged students started out with very high expectations about the likelihood that they would attend college in eighth grade but lowered them during high school as they observed changes in their grade point average (GPA).

Although these studies suggest that information about ability can affect students' educational decisions, this interpretation is based on the assumption that students derived new information about their ability from their ACT score or GPA. However, an observed behavior may be consistent with multiple beliefs and preferences. Furthermore, without baseline data on expectations, a researcher could confuse a positive information shock for a negative one when students' performance is high yet happens to be lower than what they had anticipated, and vice versa. Even when accounting for observable information available to students, as Fryer and Holden (2012) do, there could be unobservable factors leading students to make a valuation of their expected performance that differs from a researcher's valuation.[2]

In response to this identification issue, some economists have elicited self-reported beliefs from students via surveys. Stinebrickner and Stinebrickner (2012, 2014) linked longitudinal surveys to administrative data from undergraduates at Berea College to explore how students update their expectations about future academic performance in response to their college grades. The researchers concluded that fewer students would drop out of college and switch out of science majors if they did not learn about their ability. Using survey data from undergraduates at Northwestern University, Zafar (2011) similarly showed that students update their expectations in response to their college grades, which plays a role in their decision to switch majors.

A challenge to this approach is that because survey data are collected over time, the source of the new information cannot be pinned down. Although Zafar (2011) and Stinebrickner and Stinebrickner (2012, 2014) attributed their results to students learning about their ability through

[1] Researchers have found that people tend to overestimate the costs and underestimate the returns to schooling and that providing this information to disadvantaged individuals can increase their human capital investment (for example, see Nguyen 2008; Jensen 2010; Oreoupoulos and Dunn 2012; Hoxby and Turner 2013a; Dinkelman and Martinez 2014).

[2] Fryer and Holden (2012) observed that the academic performance of lower-performing students suffered after an experiment that incentivized them to take repeated practice math tests. The authors argue that this result is most likely explained by students learning that their ability was lower than they believed.

their college grades, they could not rule out other sources of information the students could have received between surveys. Furthermore, the authors could not show that the source of information, whatever it may have been, actually caused the observed change in educational investments. To address these limitations, Zafar and Wiswall (2015) designed an experiment that measured beliefs immediately before and after randomly providing students at New York University with earnings and labor supply information on various fields. They found that students revised their beliefs in response to this information, which affected their plans for their future college major. However, the authors were unable to link these changes in plans to students' observed educational decisions.

To understand whether individuals learn from and respond to a source of information, a researcher must elicit high-frequency survey data about expectations, observe an exogenous innovation in the individual's information set, and link expectations to outcomes. To my knowledge, my study is the first to determine the causal effect of a well-defined information intervention on both expectations and realized investments.

The next section of this paper describes a Bayesian learning framework to illustrate how new information about ability can affect individuals' beliefs and educational decisions. Section III explains the details of the PSAT and AP Potential signal. Section IV describes the administrative and survey data from Oakland schools. Section V includes an analysis of the survey data, and Section VI provides estimates of the causal effect of the AP Potential signal. Section VII concludes.

## II. BAYESIAN LEARNING FRAMEWORK

To explore how uncertainty about one's ability affects the decision to participate in AP, consider the case in which individuals are distinguished by unobserved ability, $\alpha_i$. The AP enrollment decision will depend on the student's best estimate of $\alpha_i$ using the information available to her at the time the decision is made. The individual forms an expectation, or self-assessment, of her ability over the course of her lifetime given a wide variety of factors, such as her grades in school and how encouraging her parents, peers, and teachers are. This self-assessment reflects her true ability with an added error term:

$$(1) \quad s_i = \alpha_i + \epsilon_i^s,$$

where $\epsilon_i^s \sim N(0, \sigma_s^2)$, and hence the self-assessment has precision $\rho^s = \frac{1}{\sigma_s^2}$. Precision here may be interpreted as how confident the student is in her self-assessment.

Providing students a new signal of their ability could affect their decision to participate in AP since the returns to that investment are increasing in the individual's ability. Consider a new signal of ability, like the PSAT, that becomes available to students at time $t+1$:

$$(2) \quad PSAT_i = \alpha_i + \epsilon_i^{PSAT},$$

where $\epsilon_i^{PSAT} \sim N(0, \sigma^2_{PSAT})$ and hence the signal has precision $\rho^{PSAT} = \frac{1}{\sigma^2_{PSAT}}$. The precision of both the prior self-assessment and the PSAT are assumed to be finite, such that they can never perfectly measure ability. With a new signal available, the individual will revise her beliefs based on the information content of the signal, $I_{i,t+1}$, which can be expressed as follows:

(3) $I_{i,t,+1} = PSAT_i - E(PSAT_i \,|\, \Omega_{i,t})$

where $\Omega_{i,t}$ denotes the information set available to the individual at time *t* and $E(I_{i,t,+1} | \Omega_{i,t}) = 0$. Under rational Bayesian learning, individuals are assumed to use all available information in forming expectations; therefore, revisions of their expectations are determined solely by new information.

Because the signal was not predictable given the information available at time *t*, the difference between the realized signal and the expected value of the signal at time *t* can be thought of as a shock.[3] When the new signal becomes available, the student uses the information content to update her expected ability:

(4) $E(\alpha_i | \Omega_{i,t+1}) = \gamma^s s_i + \gamma^I I_{i,t+1}$

where $\gamma^s = \frac{\rho^s}{\rho^s + \rho^{PSAT}} \in [0,1]$ is the weight assigned to the prior self-assessment, and similarly, $\gamma^I = \frac{\rho^{PSAT}}{\rho^S + \rho^{PSAT}} \in [0,1]$ is the weight assigned to the information shock. This last expression is a result of Bayes' rule. Intuitively, the weight assigned to each signal depends on its relative precision.

If $\gamma^I > 0$, when the PSAT becomes available, students update their expected ability according to the information content of the test. It is likely that $\rho^{PSAT} > \rho^s$, given the noisy and incomplete nature of prior sources of information about ability and that the PSAT is designed to be a nationally standardized measure of college aptitude. The magnitude of the revision depends on the relative precision and size of the information shock. More precise information shocks and more extreme information shocks both produce larger changes in beliefs.

Because individuals revise their expected ability in response to the new information signal, some may also revise their AP enrollment decision if the change in their expected ability is large enough, such that the return now exceeds the cost. Although policymakers may not fully control

[3] In reality, individuals may select into receiving the PSAT signal at time *t* + 1. In such a case, as in the absence of a testing mandate, we will observe PSAT scores only for individuals whose expected ability exceeds a threshold increasing in the costs of the test and decreasing in its value. However, under the standard Bayesian model, revisions of expected ability are affected by the information shock (that is, the deviation from the prior expectation) but not by the absolute level of performance.

the size of the information shock provided by a given information intervention, they can control the precision by providing a signal that is credible and meaningful. Finally, note that the chances of enrolling in AP under uncertainty may be lower or higher than the optimal based on full information, but having access to the PSAT signal should reduce error so that fewer students undermatch and overmatch into AP given their level of ability.

Two potential limitations of the Bayesian model could have important implications for the design and delivery of information interventions. First, whereas Bayesian updating assumes that individuals' updating behavior depends only on the magnitude and precision of new information, there is evidence that whether the shock is positive or negative matters (Eil and Rao 2011). Second, the standard Bayesian model assumes that decision makers use all available information, despite ample evidence to the contrary (DellaVigna 2009).

One way to reconcile the first limitation is to assume beliefs directly affect utility, thereby creating an incentive for optimistic self-deception that leads to asymmetric updating (Bénabou and Tirole 2002; Koszegi 2006). A second theory, developed by Rabin and Schrag (1999), assumes that individuals have a self-confirmatory bias in which there is a positive probability that they misread a signal as supporting their current belief. A third theory is that individuals are alarmists, overreacting to information they perceive to imply greater risk, potentially placing more weight on negative shocks (Viscusi 1997; Cameron 2005).

The second limitation can be addressed by theories of inattention that propose that individuals imperfectly integrate publicly available information into their decision making. These theories have been widely used in macroeconomic research to help explain the sluggish response of inflation to monetary policy (for example, Mankiw and Reis 2002; Sims 2003; and Reis 2006). Individuals may process information only partially or only perceive the information with some probability depending on factors like salience and complexity (Chetty et al. 2009; DellaVigna 2009; and Karlan et al. 2010). Models of inattention can thus be reframed as Bayesian learning in which less salient or more complex information has a higher cost of acquisition or processing.[4] If a student misses the AP Potential message at the bottom of the report, she is unlikely to respond to information that is potentially valuable and seemingly readily available.

## III. AP POTENTIAL

Although standardized testing is not the only way to measure and provide information about ability, it is reliable and scalable. For this reason, there is a long history in education of using standardized testing specifically to communicate information about ability. Novick (1970) wrote of the possibility that an assessment could provide an individual with "information about himself" to make better educational decisions.

[4] Recently, empirical work has confirmed the importance of information complexity (Dynarski and Scott-Clayton 2006; Pope 2007; Bhargava and Manoli, 2015) and salience (Finkelstein 2009; Chetty et al. 2009) in markets as diverse as education, health, transportation, and retail.

Among other uses, the PSAT provides information about high school students' aptitude for AP, a national program that offers college-level courses and exams during high school.[5] Students typically take the PSAT during their sophomore and junior years of high school and take AP courses during their junior and senior years. These AP courses are taught by teachers specially trained in the AP curriculum for their subject. Students who take AP courses can also take corresponding exams administered by the College Board. Nationally, more than 90 percent of four-year colleges grant students credit, placement, or both on the basis of successful AP exam scores (United States Department of Education 2015). [6] Most selective colleges have come to expect AP or other advanced coursework in students' transcripts.[7]

After finding that PSAT scores are strongly correlated with performance on most AP exams, much more so than high school GPA or grades in prior relevant courses (Camara and Millsap 1998), the College Board developed the AP Potential signal. Researchers selected the measure with the highest correlation to performance on each AP exam from among seven possible combinations of PSAT scores: reading ($R$), mathematics ($M$), writing ($W$), $R + M$, $R + W$, $M + W$, and $R + M + W$.[8] A binary AP Potential signal for each of 27 AP subjects was defined using the cut-point score that corresponded to passing that AP exam with at least a 60 percent probability (see Table A.1 in the appendix for the scores and cut-points used to define AP Potential for each AP subject).

In 2013 and 2014, the College Board added a message about AP Potential to the Next Steps section of the paper PSAT score report that every student receives.[9] Based on whether they met at least one AP Potential criterion, students were either given a congratulatory message stating they had potential to succeed in one or more AP courses or received a general message about speaking to their counselor to learn more about AP (Figure 1). The message was placed at the bottom of the report and occupied less than two percent of the report's total area (see Figure A.1 for a sample report from 2014). The rest of the report contained multiple measures of the student's performance on the PSAT.

[5] The PSAT page on the College Board website tells students, "Your test results will let you know which AP courses you should check out."

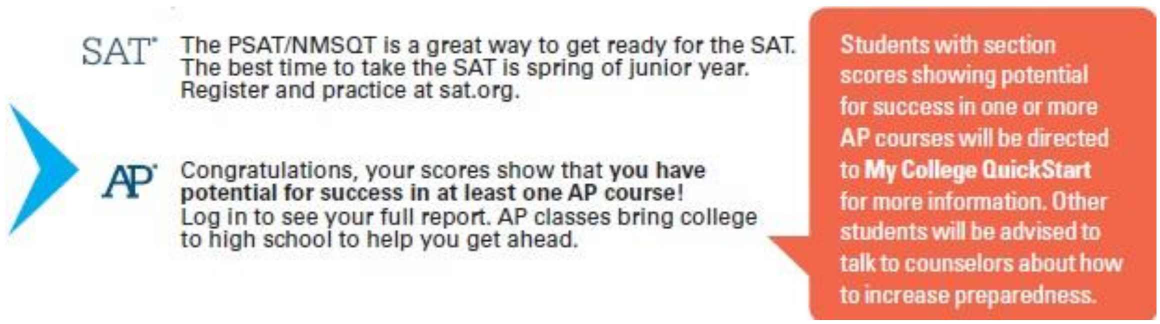
[6] AP exam scores range from 1 to 5, and a score of 3 or above typically qualifies students to receive college credit.

[7] In the University of California system, for example, fewer than 10 percent of applicants take no AP or honors courses in high school (Geiser and Santelices 2006).

[8] The PSAT did not have a writing section until 2006, so AP Potential cut-point scores were adjusted in 2007 using research by Ewing et al. (2007) to include writing scores.

[9] Following the 2015 redesign of the PSAT, the new paper reports no longer contain the AP Potential signal, although students are still prompted to go online to "see which AP courses may be a good match." Students may find their AP Potential on a course-by-course basis online.

**Figure 1. 2013 PSAT results report, Next Steps section**




## IV. DATA

### Administrative data

The administrative data for this paper were provided by the Oakland Unified School District, a medium-sized, urban school district in northern California. The data span all students enrolled in non-charter high schools between the 2008 (2008–2009) and 2014 (2014–2015) academic years, although the analysis focuses on students who were in 10th grade in 2013, the first year the AP Potential signal became available on PSAT reports.[10] In 2013, more than two-thirds of high school students in the district were eligible for free or reduced-price lunch and more than 90 percent were non-white (Table 1).

Comparing the share of students who met the AP Potential criteria in grade 10 (18 percent) to the share of students who participated in AP courses in grades 11 or 12 (37 percent) suggests that more students enrolled in AP courses than had AP Potential. Indeed, although students with AP Potential were more than twice as likely as students without AP Potential to take AP courses and exams, some mismatch remained. About 16 percent of students who met the signal's criteria did not enroll in AP courses, while 40 percent of students who did not meet the signal's criteria did enroll. Students with AP Potential who took an AP exam were 3.3 times more likely to pass than students without AP Potential, who had a pass rate of 22 percent. Though there are other factors like student interest and motivation that should determine enrollment in advanced coursework, in the presence of resource constraints schools and students do not appear to be fully utilizing information about ability.

[10] All years refer to academic years henceforth.

### Table 1. Summary statistics of Oakland High School students, 2013

| | (1) All Students | (2) AP Potential | (3) No AP Potential |
|---|---|---|---|
| Black | 0.360 | 0.159 | 0.368 |
| Latino | 0.354 | 0.183 | 0.397 |
| Asian | 0.162 | 0.289 | 0.155 |
| White | 0.076 | 0.319 | 0.032 |
| Female | 0.478 | 0.559 | 0.495 |
| Eligible for F/R Lunch | 0.680 | 0.458 | 0.762 |
| English Learner | 0.213 | 0.023 | 0.208 |
| Took the PSAT in Grade 10 | 0.726 | | |
| Grade 10 PSAT Test-Takers with AP Potential | 0.181 | | |
| Took AP Classes in Grade 11 or 12 | 0.366 | 0.838 | 0.396 |
| Took AP Exams in Grade 11 or 12 | 0.268 | 0.743 | 0.276 |
| AP Test-Takers who Passed in Grade 11 or 12 | 0.449 | 0.734 | 0.223 |
| Graduated in Grade 12 | 0.675 | 0.922 | 0.753 |
| Graduates Enrolled in 4-year College | 0.296 | 0.676 | 0.288 |
| N | 9196 | 985 | 3555 |

### Survey data

To identify how information affects students' beliefs, I gathered survey data from 10th grade students who took the PSAT in October 2013 at Oakland Technical High School, Oakland's largest secondary school. It houses about 2,100 students, 37 percent black, 22 percent white, 19 percent Asian, and 18 percent Latino. The school was selected based on its size and the willingness of school administrators to participate in the study.

The survey instrument (see Figure A.2 in the appendix) was designed with the Bayesian framework outlined in Section II in mind.[11] In the first part, students assessed their expected relative performance on the PSAT and their relative academic ability. Students selected one of five categories: "lowest 10%" (coded as 0), "below average" (coded as 1), "average" (coded as 2), "above average" (coded as 3), and "highest 10%" (coded as 4).[12] Students also reported their confidence in their responses. In part 2, students indicated their belief that a particular academic outcome would occur (for example, that they would attend a four-year college). Students stated their expectation by selecting one of four categories, ranging from "not at all likely" to "very

[11] Much of the survey wording was adapted from the Higher Education Research Institute's Freshman Survey, which is administered to thousands of college freshmen nationwide each year.

[12] Students were asked to rate their performance and their ability relative to other students at the same high school to reduce measurement error and simplify the question.

likely." In the case of AP course enrollment, students gave the explicit number of courses they planned to take.[13, 14]

After students filled out the baseline survey, I passed out their PSAT score reports and an informational handout that I created. The handout contained a conversion table to help students predict their SAT scores using their PSAT scores, a table listing the SAT score ranges of admitted students at all the four-year public colleges in California, and a list of the AP courses offered at the school (see Figure A.3 in the appendix). Next, I briefly explained the report and handout, following the same script. I ended by asking students to check whether they had received the AP Potential message. Students also had a chance to ask questions.[15] This process took approximately 10 minutes. Students then completed the endline survey, which contained the same questions as the baseline survey.

Of 528 10th graders who took the PSAT at the school (92.6 percent of the sophomore class), 440 students took at least one of the surveys and 337 students took both the baseline and endline. This sample size is comparable or greater to those in similar studies, such as Zafar (2011) and Stinebrickner and Stinebrickner (2012). However, survey participants differed from the population of PSAT test-takers (Table 2).[16] Students who took both surveys were more likely to be female and Asian and less likely to be black. They had total PSAT scores that were on average 6.5 points higher (about 0.2 standard deviations) relative to other Oakland students. As a result, they were more likely to receive the AP Potential signal.

Although the primary goal of the survey analysis is to characterize individual behavior, not estimate magnitudes, it is worth discussing how the sample selection could affect results. The average information shock is larger, and more negative, for students with lower levels of performance on the PSAT, who were less likely to complete both surveys. This relationship suggests that students who did not take both surveys likely experienced negative shocks, on average. As a result, the main concern is whether individuals deviate from the Bayesian framework and respond asymmetrically to negative versus positive shocks or exhibit heterogeneous responses depending on individual characteristics. I explore these possibilities in the next section.

[13] Rather than ask students for percentile rankings or expected probabilities, I asked them to select from categories. Oakland educators who provided feedback on the survey instrument agreed that percentiles and probabilities were not adequate concepts to include in the survey. In addition, some concern exists that the open-ended response mode, requiring students to provide their own numbers, could increase the rate of respondents using 50 percent to express uncertainty (de Bruin et al. 2000).

[14] In Part 3, the survey asked about planned time expenditures. However, many students left this section partially or completely blank, so I ignore it in the analysis that follows. This question was intended to measure expected academic effort and students' tastes for academic versus nonacademic activities.

[15] Interestingly, the most common question I received was whether or not students had "passed" the PSAT, suggesting they were looking for a less complex way to assess their performance.

[16] Three students who took both surveys but did not take the PSAT are excluded from column 3 in Table 2.

**Table 2. Survey participants compared to the 10th grade population**

| | (1) All 10th Graders | (2) Took PSAT | (3) Took Both Surveys |
|---|---|---|---|
| Female | 0.508 | 0.520 | 0.564 |
| Black | 0.374 | 0.357 | 0.294 |
| Latino | 0.211 | 0.211 | 0.199 |
| Asian | 0.167 | 0.175 | 0.217 |
| White | 0.223 | 0.231 | 0.255 |
| Eligible for F/R Lunch | 0.488 | 0.485 | 0.469 |
| AP Potential | | 0.415 | 0.496 |
| Total PSAT score | | 128.5 | 135.0 |
| | | (32.85) | (31.73) |
| N | 569 | 528 | 337 |

## V. SURVEY RESULTS

### Information shocks

The change in the individual's expectation between time $t$ and time $t + 1$ is a function of the information shock experienced between the two periods, which can be expressed as follows:[17]

$$I_{i,t+1} = E(PSAT_i | \Omega_{i,t,+1}) - E(PSAT_i | \Omega_i, t) \quad (5)$$

Recall that surveyed students rated their relative PSAT performance before and after receiving their PSAT score reports using five categories, ranging from "lowest 10%" to "highest 10%." Approximately 30 percent of students experienced a negative information shock, downgrading their self-assessed relative performance on the PSAT; 18 percent experienced a positive information, upgrading their self-assessment; and the remaining 52 percent of students did not experience an information shock, as defined by this measure. In Table 3 I summarize how students changed their responses from time $t$ to $t+1$.

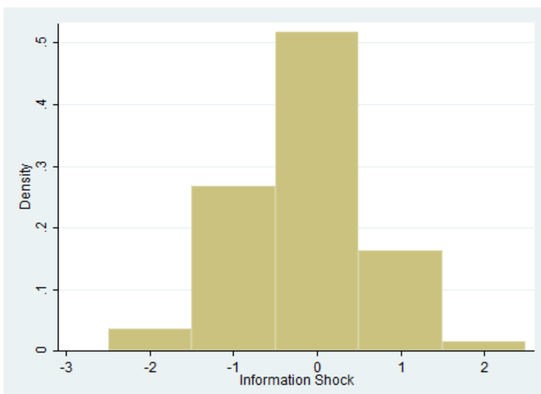
[17] Given that students' performance on the PSAT is realized at time $t$ + 1, an alternative would have been to define the information value of the PSAT as $I_{i,t+1} = PSAT_i - E(PSAT_{i,t+1}|\Omega_i, t)$ as in equation 3. Under complete information about everyone's performance, the two options should be identical. However, even after receiving their results, students still provided their "best guess" of their relative performance.

**Table 3. Revisions in self-assessed PSAT performance**

| | | Time *t+1* | | | | | |
|---|---|---|---|---|---|---|---|
| | | Lowest 10% | Below average | Average | Above average | Highest 10% | N |
| Time *t* | Lowest 10% | | | | | | 0 |
| | Below average | 15% | 53% | 26% | 6% | | 53 |
| | Average | 2% | 30% | 49% | 18% | 1% | 179 |
| | Above average | | 8% | 26% | 58% | 9% | 78 |
| | Highest 10% | | | 13% | 31% | 56% | 16 |
| | N | 12 | 88 | 123 | 85 | 18 | 326 |

Using these ordinal responses, I calculated a value for each student's information shock according to equation 5. Across the sample, this metric varies from –2 (an extreme negative surprise, in which the student downgraded her self-assessment by two categories) to 2 (an extreme positive surprise, in which the student upgraded her self-assessment by two categories; see Figure 2).

**Figure 2. Distribution of information shock**




To verify that students revised their beliefs consistent with the information they received, I regressed the information shock against students' AP Potential status, PSAT score, and gender and ethnicity:[18]

$$(6)\quad I_{i,t+1} = \beta_0 + \beta_1\, AP\ Potential_i + \beta_2 PSAT\ Score_i + \beta_3\, Female_i + \textstyle\sum_j \beta_j\, Ethnicity_{i,j} + \mu_i$$

Higher PSAT scores and the AP Potential signal resulted in more positive information shocks (Table 4). Further, students with the same total PSAT score who received the AP Potential signal experienced a larger information shock, which suggests that the AP Potential signal contained information *in addition to* that provided by the scores. Although there were differences in the average information shocks experienced by different genders and ethnic

[18] The excluded ethnic group is white students.

groups, once PSAT scores and AP Potential status were controlled for there were no statistically significant differences.

**Table 4. Factors affecting the information shock**

| DV: Information Shock | (1) | (2) |
|---|---|---|
| AP Potential | 0.337** | 0.316** |
| | (0.143) | (0.153) |
| PSAT Score | 0.009*** | 0.008** |
| | (0.003) | (0.003) |
| Black | | -0.195 |
| | | (0.131) |
| Latino | | -0.029 |
| | | (0.138) |
| Asian | | -0.129 |
| | | (0.117) |
| Female | | 0.098 |
| | | (0.082) |
| $R^2$ | 0.194 | 0.208 |
| N | 326 | 314 |

Note: Students rated their relative abilities and PSAT performance before and after receiving their score reports using five categories: “lowest 10%” (coded as 0), “below average” (coded as 1), “average” (coded as 2), “above average” (coded as 3), and “highest 10%” (coded as 4).

*significant at 10%

** significant at 5%

*** significant at 1%

### Revisions of self-assessed ability

Students were asked to assess their overall academic ability *A* and their ability in the areas tested by the PSAT: mathematics *M*, reading *R*, and writing *W*. To check for Bayesian learning, I approximate equation 4 (Bayes’ rule) for each ability self-assessment using the following regression model:

$$(7)\quad \mathrm{E}(\alpha_i\,|\,\Omega_{i,t+1}) = \gamma^s\,\mathrm{E}(\alpha_i\,|\,\Omega_{i,t}) + \gamma^I I_{i,t+1} + \eta_i$$

where, as before, $\gamma^s$ is the weight assigned to the individual’s prior self-assessment and $\gamma^I$ is the weight assigned to the information shock received from the PSAT. The coefficients $\gamma^s$ and $\gamma^I$ show the nature of the updating process. For example, $\gamma^s$ would equal one and $\gamma^I$ would equal zero if the student depended solely on her prior information and did not learn any new information from the PSAT relevant to her academic self-assessments.

These estimates show that $\hat{\gamma}^s$ is consistently smaller than one and that the information shock is a statistically significant factor in students’ posterior self-assessment of their academic, math, reading, and writing ability (Table 5). The theoretical prediction that the information weights will sum to one in the case where the new information is all that is consequential is borne out in the results. The value of new information relative to the prior can be denoted as

$V = \dfrac{\rho^{PSAT}}{\rho^{S}} = 1/\gamma^{S} - 1$, the ratio of the precision of the new information (its perceived relevance) to the precision (or degree of confidence) of the prior. The results suggest that students found the information provided by the PSAT to be most valuable for their revision of their reading and writing ability (Table 5).

**Table 5. Bayesian updating of self-assessed ability**

| | (1) Academict+1 | (2) Matht+1 | (3) Readingt+1 | (4) Writingt+1 |
|---|---|---|---|---|
| Prior Belief | 0.736*** | 0.729*** | 0.642*** | 0.686*** |
| | (0.033) | (0.029) | (0.038) | (0.035) |
| Information | 0.266*** | 0.288*** | 0.375*** | 0.325*** |
| Shock | (0.041) | (0.036) | (0.052) | (0.044) |
| $R^2$ | 0.947 | 0.934 | 0.920 | 0.924 |
| N | 324 | 324 | 324 | 325 |
| V | 0.359 | 0.372 | 0.558 | 0.457 |

Note: Students rated their PSAT performance and relative abilities before and after receiving their score reports using five categories: "lowest 10%" (coded as 0), "below average" (coded as 1), "average" (coded as 2), "above average" (coded as 3), and "highest 10%" (coded as 4).

*significant at 10%

** significant at 5%

*** significant at 1%.

Individuals who are more confident in their self-assessment are expected to update less in response to new information. I re-estimate equation 7 separately for students who were most confident ("very sure" or "practically certain") in their prior self-assessment and those who were least confident (only "somewhat sure" or "not sure at all"). As predicted, students who reported being less confident in their priors placed smaller weights on their priors than those who reported being most confident (Table 6). The estimated weights on the prior belief used by the most and least confident students are statistically significantly different at the 10 percent level or better in each pair of regressions, except for mathematics. The new information was thus more valuable to those individuals who were least sure of their prior beliefs, as reflected in the estimates of *V*.

The results thus far suggest that students responded rationally to the receipt of new information in revising their self-assessed abilities. However, Bayesian learning is difficult to reject empirically. As discussed earlier, departures from the Bayesian benchmark have been documented in other settings. Understanding which heuristics students use, if any, in processing new information can inform the design and delivery of similar information interventions.

To test for deviations from Bayesian learning, I look for evidence of heterogeneity in updating behaviors, asymmetric responses to shocks of different signs, and self-confirmatory bias in revisions. These results appear in Tables A.2-A.4 in the Appendix. I find no statistically significant evidence of heterogeneity in students' revisions of their academic ability by prior beliefs or individual characteristics. [19] There is also no evidence that the sign of the shock matters, which would have suggested optimistic or alarmist tendencies. Finally, I test for self-confirmatory bias. Students with low-ability priors responded similarly to positive and negative shocks, whereas students with high-ability priors had stronger responses to negative shocks that disconfirmed good news. These results are suggestive of an alarmist response, but only among those who initially believed they had above average ability.

**Table 6. Bayesian updating of self-assessed ability, by confidence in prior**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | $\text{Academic}_{t+1}$ | | $\text{Math}_{t+1}$ | | $\text{Reading}_{t+1}$ | | $\text{Writing}_{t+1}$ | |
| | Most Confident | Least Confident | Most Confident | Least Confident | Most Confident | Least Confident | Most Confident | Least Confident |
| Prior Belief | 0.755*** | 0.554*** | 0.791*** | 0.699*** | 0.687*** | 0.318* | 0.759*** | 0.363*** |
| | (0.043) | (0.107) | (0.038) | (0.073) | (0.053) | (0.161) | (0.052) | (0.113) |
| Information Shock | 0.246*** | 0.301*** | 0.188*** | 0.290*** | 0.352*** | 0.578*** | 0.231*** | 0.512*** |
| | (0.056) | (0.104) | (0.051) | (0.067) | (0.082) | (0.182) | (0.072) | (0.097) |
| $R^2$ | 0.953 | 0.899 | 0.941 | 0.939 | 0.931 | 0.847 | 0.938 | 0.831 |
| N | 156 | 32 | 156 | 37 | 171 | 29 | 157 | 31 |
| V | 0.325 | 0.804 | 0.265 | 0.432 | 0.456 | 2.15 | 0.317 | 1.756 |

Note: Students rated their relative abilities and PSAT performance before and after receiving their score reports using five categories: “lowest 10%” (coded as 0), “below average” (coded as 1), “average” (coded as 2), “above average” (coded as 3), and “highest 10%” (coded as 4).

*significant at 10%

** significant at 5%

*** significant at 1%.

## Revisions of expected future outcomes

The survey asked about the expected likelihood of the following binary outcomes: passing the graduation exit exam in the first attempt, taking the SAT, graduating from high school, and attending community college or a four-year college. Students also stated the number of AP classes they expected to enroll in the following year. Since Bayesian learning appears to provide an appropriate characterization of students' response to new information, I proceed to re-estimate equation 4 (Bayes' Rule) for these academic expectations.

Estimates of the weights students placed on their prior expectations and the information shock reveal that the new information was most valuable for the AP enrollment decision (Table 7). Students’ prior expectations continued to play a significant role, as expected. However, this

[19] I repeat this analysis for the other self-assessed ability measures and similarly find no evidence of heterogeneity in revisions, with one exception. In contrast to males, female students hardly adjusted their self-assessed math ability in response to the shock. This result is consistent with past research that suggests women’s perceptions of math ability are more fixed than men’s (Dweck, 2008). (Results not shown.)

relationship was weakest for the number of AP classes students expected to enroll in, with students incorporating the new information most strongly for this decision.[20]

**Table 7. Bayesian updating of expected academic outcomes**

| | (1) APt+1 | (2) GradTestt+1 | (3) TakeSATt+1 | (4) GradHSt+1 | (5) CommCollt+1 | (6) 4Y rCollt+1 |
|---|---|---|---|---|---|---|
| Prior Belief | 0.654*** | 0.866*** | 0.878*** | 0.931*** | 0.836*** | 0.839*** |
| | (0.081) | (0.033) | (0.036) | (0.017) | (0.043) | (0.031) |
| Information Shock | 0.232*** | 0.173*** | 0.167*** | 0.077*** | 0.127*** | 0.188*** |
| | (0.050) | (0.046) | (0.049) | (0.023) | (0.034) | (0.039) |
| $R^2$ | 0.839 | 0.966 | 0.963 | 0.986 | 0.829 | 0.962 |
| N | 270 | 315 | 323 | 318 | 315 | 324 |
| V | 0.530 | 0.155 | 0.139 | 0.075 | 0.196 | 0.192 |

Note: Students rated their relative abilities and PSAT performance before and after receiving their score reports using five categories: "lowest 10%" (coded as 0), "below average" (coded as 1), "average" (coded as 2), "above average" (coded as 3), and "highest 10%" (coded as 4).

*significant at 10%

** significant at 5%

*** significant at 1%.

Revisions of self-assessed ability did not always mirror revisions of expected outcomes for a number of reasons. First, the information proved to have differing value across the various outcomes, reflecting what was emphasized in the report and presentation (AP enrollment). Second, the shocks were likely relevant for students at different margins of ability depending on the outcome. A high-ability student who received a negative shock may have rightly concluded that she was in no danger of failing to graduate from high school, for example, even if she reduced her self-assessed ability. Finally, students likely took factors other than ability into account as they considered the likelihood of various outcomes.

## VI. THE CAUSAL IMPACT OF THE AP POTENTIAL SIGNAL

Although the AP Potential signal contained new information about ability that students used to rationally adjust their plans to enroll in AP classes, students may have just been temporarily uplifted or demotivated, leaving outcomes unchanged. Students' reported plans could also reflect self-presentation motives that led them to inflate their true intentions. Despite these concerns, experimental evidence from psychology shows that interventions producing statistically significant increases in intentions also produce significant increases in behavior (Webb and Sheeran 2006).

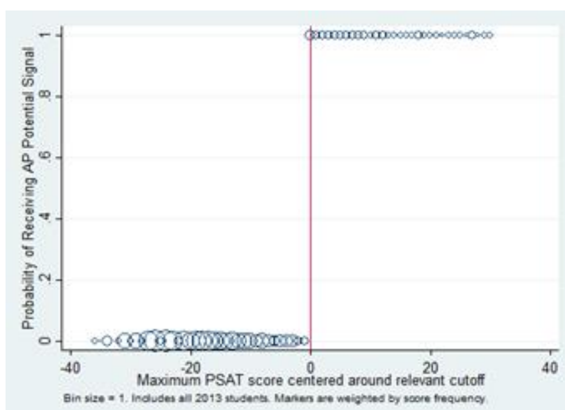
[20] In a separate analysis presented in Table A.5 in the Appendix, I find that revisions of expectations about AP course-taking were driven by students who received a positive information shock.

Survey expectations and actual enrollment the following year were in fact positively correlated, with a correlation coefficient of 0.55.[21] However, students were overoptimistic in their stated plans. On average, students said they would take 1.2 AP classes but mean course enrollment was 0.41. Students who upwardly revised their expectations in response to the information shock did, however, enroll in more AP classes compared to those who did not.[22] These comparisons show that self-reported beliefs are meaningful but cannot be assumed to fully reflect future outcomes. Thus, this section focuses on rigorously identifying the causal effect of the AP Potential signal on AP course and exam taking the following year.

## Identification strategy

The deterministic nature of the assignment of the AP Potential signal allows for a sharp regression discontinuity (RD) design to estimate its effect. In the sharp RD design, the treatment $Treat_i$ is a deterministic function of an assignment variable $R : Treat_i = 1R_i \geq c$. As explained earlier, succeeding in meeting just 1 of 27 conditions (see Table A.1 in the appendix) would result in the student receiving the AP Potential message on her score report. Therefore, the maximum value of each student's re-centered set of scores can be thought of as the "binding" score for that student. Using data from all 10th grade students in Oakland in 2013, I confirm that the relationship between the binding score and the probability of receiving the signal is completely deterministic (Figure 3).

**Figure 3. Deterministic relationship between AP Potential and R**




The sharp RD design exploits the discontinuity in the conditional expectation of the outcome given the assignment variable to uncover an average causal effect of the treatment:

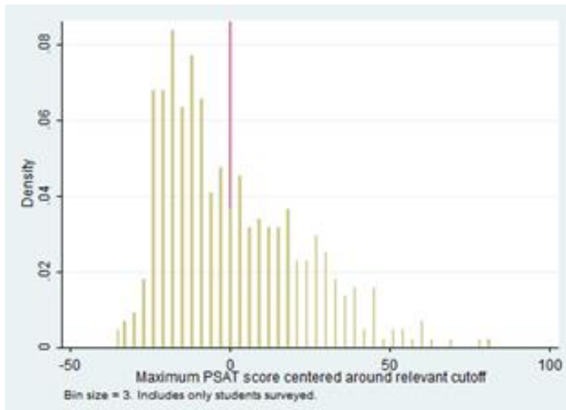
(8) $\lim_{x \to c} E[Y_i | R_i = r] - \lim_{x \leftarrow c} E[Y_i | R_i = r]$

[21] In a meta-analysis of 185 studies of intentions and behavior, Armitage and Connor (2001) found that the average correlation between measures of intention and future behavior was 0.47.

[22] Of the 440 students who participated in the survey in any form (regardless of whether they filled out both the baseline and endline), 12 students did not return to the district the following year. At 2.7 percent, this attrition rate is uncorrelated with demographic characteristics or PSAT performance.

which can be interpreted as the average causal effect of the treatment at the discontinuity point: $\tau = E[Y_i(1) - Y_i(0) | R_i = c]$ (Imbens and Lemieux 2008). By design, there are no individuals with $R_i = c$ for whom we observe $Y_i(0)$. RD exploits the fact that we observe units with values of the assignment variable arbitrarily close to *c*, provided that a smoothness assumption about the distribution of this variable holds. A bin size of 3 is small enough to show how the binding test score data behave but not so small that it introduces unnecessary noise; using this bin size, there are no visible discontinuities in the distribution of this score around the cut-point (Figure 4).[23]

**Figure 4. Distribution of re-centered binding test score, R**




Because treatment is perfectly correlated with observable characteristics (PSAT scores), the continuity of unobserved characteristics is sufficient to allow identification of the average treatment effect for marginal students. I graph various non–outcome variables as a check of the orthogonality of unobservables (Appendix Figure A.4). No discontinuities are visible, which is consistent with the deterministic nature of the assignment rule. Finally, note that participating in the survey did not provide a differential treatment to students *at the margin* of AP Potential. Although surveyed students were positively selected, the probability of participating in the survey did not jump at the cut-point (Appendix Figure A.5).[24]

Next I graph the probability that students enrolled in at least one AP course, the average number of AP courses they enrolled in, and the average number of AP courses they passed in the academic year following the PSAT (Figure 5).[25] The graphs on the left show the relationship between these outcomes and the assignment variable just for students who participated in the

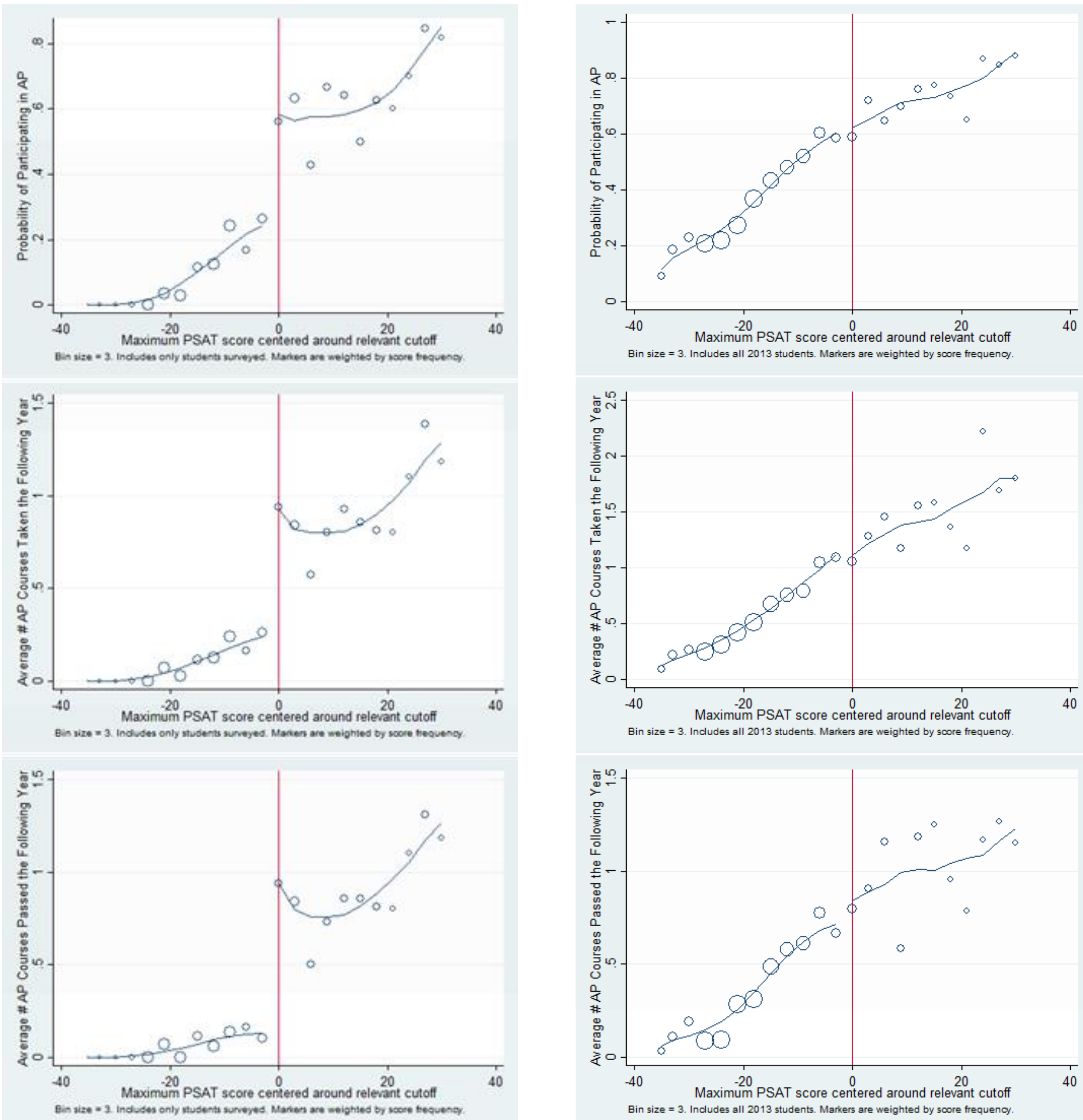
[23] A bin sizes of 3 was selected as an optimal bin size for analysis using both visual inspection and more formal methods. I employ the same bin sizes for all graphical displays, even those not graphing the outcome variable, in order to facilitate comparisons.

[24] The score reports at Oakland Tech were locked in the principal's office until I picked them up and remained sealed until they were opened by the students. When students receive their PSAT results, the reports are closed, showing only the student's name.

[25] The graphs illustrate that enrolling and passing an AP course are highly correlated. I examine both outcomes to explore whether the signal could push students to enroll but later drop or fail the course.

## Figure 5. AP Course participation and number of AP classes taken and passed a year later

**Surveyed Students Only** **All Students**



survey. A distinct jump is visible at the cut-point, offering evidence that receiving the AP Potential signal led students on the margin to enroll in and pass more AP classes. This finding is consistent with the survey results from the previous section. Because no survey data are required for this analysis, I expand the sample to include all students who took the PSAT in 2013. The graphs on the right depict the same outcomes for students across the district. No distinct jumps are discernable in these graphs.[26]

### Nonparametric estimates

Nonparametric estimation methods like local linear regression reduce the chances that bias will be introduced by using a much smaller portion of the data where the relationship between the assignment variable and the outcome is modeled correctly. Local linear regression is equivalent to estimating the following regression model on a subset of the data in the neighborhood of the cut-point using a weighting function:

(9) $$Y_i = \alpha + \beta_0 Treat_i + \beta_i R_i + \beta_2 R_i Treat_i + \in_i$$

Y represents three outcomes: participating in AP coursework, the number of AP courses enrolled, and the number of AP courses passed. For the choice of bandwidth, I implement the Imbens and Kalyanaraman (2009) "plug-in" procedure, which yields an optimal bandwidth of 4 for all three outcomes. Using a kernel with compact support rules out sensitivity to outlying observations, so I employ a triangle kernel. Effects are estimated separately for surveyed students and the population of 2013 test-takers.

The optimal bandwidth of 4 yields statistically significant results for all three outcomes among surveyed students (Table 8). Point estimates indicate that receiving the AP Potential signal increased the probability that a surveyed student participated in AP by 49.2 percentage points. Surveyed students who received the signal enrolled in approximately one more AP class on average. Despite the possibility that students induced into AP could drop or fail AP courses, the results are consistent when examining the number of AP courses passed at the end of the academic year. These impacts are meaningfully large because only 26.3 percent of surveyed students one bin to the left of the cut-point participated in AP. Estimates based on all 2013 students are consistently small and statistically insignificant, even at larger bandwidths.[27]

[26] Cell means are higher for all students than for surveyed students with similar values of *R* because students at Oakland Tech are higher performing than students at other high schools in the district, and thus those who participate in AP at the school are more positively selected than elsewhere in the district.

[27] Since the graphical representation showed some curvature for the surveyed sample, we may expect the results of local linear estimation to be sensitive to the choice of bandwidth. Figure A.6 in the Appendix graphs the relationship between the bandwidth size and the estimates on the number of AP course enrollments among surveyed students using a triangle kernel (left panel) and rectangular kernel (right panel). The estimates are not very sensitive.

**Table 8. Non-parametric estimates of impact of AP potential on AP course enrollment**

| Bandwidth | AP Participation | # AP Courses Enrolled | # AP Courses Passed |
|---|---|---|---|
| **Surveyed Students Only** | | | |
| 3 | 0.787***<br>(0.222) | 1.246***<br>(0.447) | 1.186***<br>(0.433) |
| 4 | 0.492*<br>(0.274) | 1.050**<br>(0.437) | 1.108***<br>(0.413) |
| 5 | 0.434*<br>(0.270) | 0.914**<br>(0.414) | 1.072***<br>(0.390) |
| **All 2013 Students** | | | |
| 3 | -0.131<br>(0.180) | -0.406<br>(0.777) | -0.172<br>(0.899) |
| 4 | -0.147<br>(0.204) | -0.372<br>(0.561) | -0.349<br>(0.549) |
| 5 | -0.100<br>(0.162) | -0.253<br>(0.423) | -0.209<br>(0.473) |

*significant at 10%

** significant at 5%

*** significant at 1%.

## Encouragement versus discouragement mechanisms

Although the survey analysis showed that the information shock was used to update expected AP course enrollment only by students who experienced a positive shock, it is possible that nearly identical students who just missed receiving the signal could have been hurt.[28] Students to the left of the cut-point may have felt discouraged from taking AP courses rather, or in addition to, students to the right of the cut-point feeling encouraged to participate.

I exploit the fact that 2013 was the first year the AP Potential message was published on PSAT score reports to build a pre-treatment comparison group of students that can serve as a counterfactual. As long as student and school characteristics did not change in the same school and grade from one academic year to the next, such a comparison should illustrate how individuals on both sides of the cut-point would have behaved in the absence of the signal.

The demographic and ability profiles of grade 10 students at Oakland Tech across 2011/12 and 2013 were remarkably stable, as were the number of AP classes offered by the school (see columns 1 and 2 of Table A.6 in the Appendix). Two exceptions arise. The first is that a greater share of students in 2013 scored proficient or advanced on the English California Standards Test (CST). However, other measures of ability, including the math CST, GPA, and share of students with AP Potential, do not differ across years. The second difference is that students in 2013 were

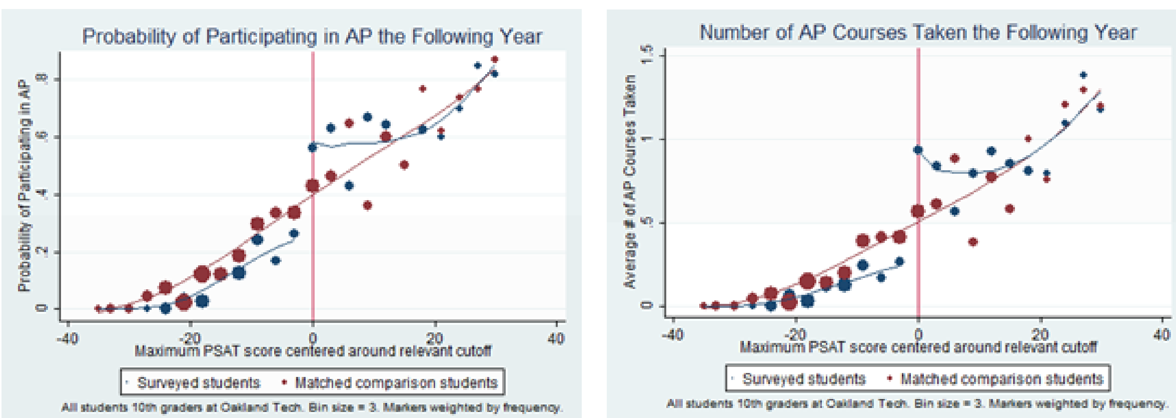
[28] Note that because students on either side of the cut-point are of indistinguishable ability, even if the signal only led to a motivational effect among those who received it, there are students who did not receive the treatment who would have similarly benefited from being nudged to participate in AP.

more likely to take the PSAT. Efforts to increase PSAT participation across the district were taking place over this period and thus this difference does not necessarily indicate other changes.

To construct a suitable comparison group for surveyed students, I draw on 10th graders at Oakland Tech from the 2011 and 2012 academic years and use propensity score matching to identify students with a similar probability of participating in the survey had the research taken place a year or two earlier. Students were matched on demographic characteristics (gender, ethnicity, English fluency, free or reduced-price lunch eligibility, and English learner status) and academic achievement (total PSAT score, English and math CST scores, and GPA). Propensity score matching was performed using one-to-one matching to the nearest neighbor with replacement. Surveyed and matched comparison students appear balanced across multiple observables (Table A.6 columns 3 and 4).

For both the probability of participating in AP and the number of AP courses taken in the year after 10th grade, the two groups behave similarly at the tails, suggesting that the students drawn from propensity score matching offer an adequate comparison group (Figure 6). This similarity also suggests that participating in the survey, which included receiving additional information in the form of the handout and being prompted to reflect on the PSAT results and future academic plans, did not in and of itself have an effect on AP course-taking.

**Figure 6. Surveyed students vs. untreated comparison students**




However, surveyed students deviated from the comparison group, which did not have access to the AP Potential signal, around the cut-point. Students near the cut-point who received the signal were more likely to participate in AP and took more AP classes than similar students in prior years. Students near the cut-point who did not receive the signal were somewhat less likely to participate in AP and took fewer AP classes than the comparison students did. Both differences are statistically significant. This analysis provides suggestive evidence that students who received the signal were motivated to participate in AP but also that some students near the cut-point who did not receive the signal were discouraged. The survey analysis did not find that students who experienced a negative shock revised their expected AP enrollment, but did show that these students consistently decreased their self-assessed ability.

### The threat of mismatch

Because the signal condenses 27 subject-specific criteria into one seemingly coarse message, students at the margin may have been nudged into AP subjects for which they were not well prepared. The three binding subjects to trigger the AP Potential signal were Spanish Literature (61.2 percent), Calculus BC (24.9 percent), and Psychology (13.5 percent), and neither Spanish Literature nor Psychology were offered at Oakland Tech or most Oakland schools, further raising the threat of mismatch. Being induced to take the wrong class could lead students to perform poorly on the corresponding AP exam or lead them to opt out of taking the exam altogether. Students could even see performance in other subjects decline. On the other hand, if the AP Potential signal is high quality and students weight it appropriately, academic mismatch should decrease and students at the margin should perform just as well.[29]

To understand subject-specific mismatch, I define a match indicator for each student-subject pairing that equals one if the student's AP course enrollment matches her AP Potential in that subject. Juniors have access to about a dozen AP courses at large schools like Oakland Tech. Comparing match rates among offered courses for 10th graders at Oakland Tech over the last six years, I find a spike of 20 percent following the introduction of the AP Potential signal. Surveyed students had a course enrollment match rate of 83 percent, with 3.5 percent of student-course enrollment pairings overmatched and 13.5 percent undermatched. Some level of undermatch is to be expected because high-ability students cannot take all the AP classes offered in a given year.

Although most students do not seem to overmatch, one result of overmatching into an AP course could be lower AP exam participation and pass rates. Nationwide, more than a third of AP students do not sit for the exams (Geiser and Santelices 2006) and about 40 percent of AP test-takers do not pass any exams (College Board 2014b). Among students in Oakland, both of these rates were above 50 percent in 2013.

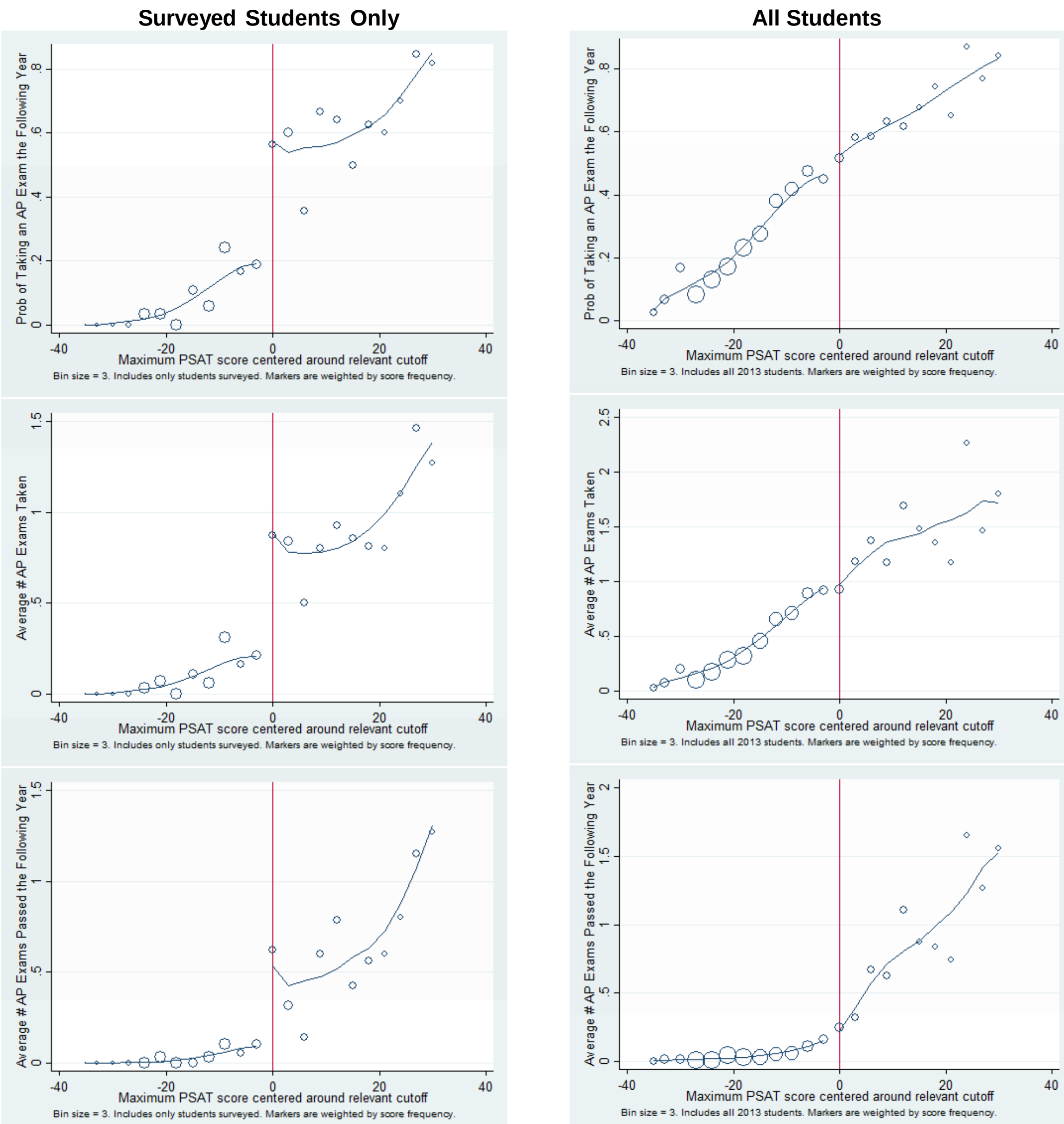
The probability of taking at least one AP exam, the average number of AP exams taken, and the average number of AP exams passed show marked jumps at the cut-point for surveyed students (Figure 7). Nonparametric estimates show that surveyed students who received the signal were 42.9 percentage points more likely to take AP exams, sitting for about one more AP exam, on average (Table 9). They also passed more AP exams, making them eligible for college credit. As before, there are no statistically significant results for the overall student population.

Conditional on taking the exam, surveyed students who received the signal performed no better or worse. Graphing average AP exam scores shows no discernable patterns around the cut-point (Figure 8). Finally, I explore the possibility that students had to shift time away from other courses to keep up with AP, resulting in a drop in their GPA. Students around the cut-point did

[29] Most of the surveyed students at the margin of AP Potential enrolled in U.S. History and Environmental Science, the most popular AP courses for juniors at the school. Nevertheless, students with Calculus BC as their binding subject were three times more likely to enroll in AP Calculus than were students whose binding subject was Spanish Literature, suggesting that students did employ other sources of information about their ability in selecting courses.

not have different nonweighted GPA at the end of the year (Figure 8).[30] The graphs indicate that the overall academic performance of students induced into AP by the signal was unaffected.

## Figure 7. AP exam participation and number of AP exams taken and passed a year later




[30] Nonweighted GPA measures course performance without adding bonus points for completing advanced coursework like AP.

### Table 9. Non-parametric estimates of impact of AP potential on AP exam performance

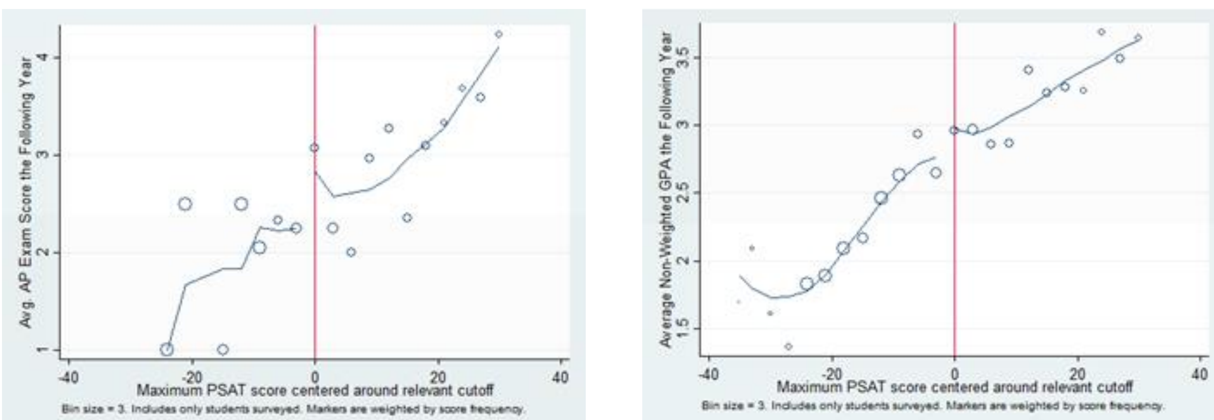
| Bandwidth | AP Exam Participation | # AP Exams Taken | # AP Exams Passed |
|---|---|---|---|
| **Surveyed Students Only** | | | |
| 3 | 0.626*** | 1.003*** | 0.730** |
| | (0.215) | (0.444) | (0.335) |
| 4 | 0.429* | 0.949** | 0.592* |
| | (0.263) | (0.452) | (0.335) |
| 5 | 0.411 | 0.879** | 0.538* |
| | (0.264) | (0.424) | (0.315) |
| **All 2013 Students** | | | |
| 3 | 0.110 | 0.084 | -0.090 |
| | (0.204) | (0.600) | (0.501) |
| 4 | 0.094 | 0.035 | -0.112 |
| | (0.187) | (0.495) | (0.361) |
| 5 | 0.107 | 0.001 | -0.077 |
| | (0.170) | (0.419) | (0.301) |

*significant at 10%

** significant at 5%

*** significant at 1%.

### Figure 8. End-of-year performance outcomes: average AP exam score and non-weighted GPA




## VII. DISCUSSION

The findings in this paper support what Becker posited in 1975: young people are uncertain about their ability and thus may not form accurate expectations of their return to educational investments. However, providing information can lead individuals to learn about their ability, update their expectations, and ultimately increase their level of investment. This type of low-cost intervention may be especially helpful for students from disadvantaged backgrounds. Among students in the Oakland school district who met the AP Potential criteria, 35 percent of black students and 27 percent of Latino students never enrolled in AP, a key step on the path to a selective college, compared to fewer than 10 percent of comparable white and Asian students.

In the present case, providing a simple but customized message to qualified candidates early in their high school careers proved to be a cost-effective way to reduce academic mismatch in AP participation. Surveyed students on the margin of receiving the signal were 49 percentage points more likely to participate in AP, enrolling in and passing approximately one more AP course their junior year. Three-quarters of these students belonged to underrepresented minority groups or low-income families. At the end of the academic year, these students also became substantially more likely to take an AP exam and passed a higher number of exams, increasing their eligibility for college credit.

As important is the finding that only students who participated in the survey exhibited a behavioral response to the signal. Although the survey analysis showed that Bayesian learning is an appropriate representation of how individuals process new information about their ability, the RD results suggest that one key assumption was violated: students who were not surveyed did not utilize the information available to them. The comparison between surveyed students and similar students in prior years who were not exposed to the AP Potential signal suggested that there was no overall survey effect. Instead, the survey and handout appear to have called attention to the signal, increasing its salience. [31] Students' inattention to the signal is not altogether surprising. The AP Potential message was not especially conspicuous on PSAT reports, nor was it clear that there were two different messages students could receive.

This finding is consistent with the growing literature on information provision. A close example is Foote et al. (2015), who found that a binary "college readiness" signal on ACT reports had no effect on students' college enrollment decisions. The authors point out that the message, which was largely inconspicuous on the report, likely had low salience. As another example, Hoxby and Turner (2013b) documented that about 60 percent of students who participated in the Expanding College Opportunities intervention designed by the authors could not recall seeing the materials at all. The authors suggested that "organizations [like the College Board and ACT] would likely achieve greater effects if they sent the materials at the same time that students received their PSAT, SAT, PLAN, or ACT scores—since score reports are extremely likely to be opened." However, the results of this paper and Foote et al. (2015) warn that this alone may not increase salience sufficiently. My findings indicate that score reports may only be effective conduits if there is an additional element that increases the salience of the information. Otherwise, students may still miss it.

Past empirical studies that have found responses to information on beliefs or behaviors typically ensured that individuals accessed the information, often through highly stylized means. For example, in Viscusi and O'Conner (1984), study participants could not proceed with the survey until they were able to answer questions that tested whether they had read the information on chemical labels provided by the experiment. In Jensen (2010), enumerators provided earnings

[31] Another possible explanation for the difference in response between surveyed students and all other students is that there was a selection effect. As noted, surveyed students were positively selected from the school and district. However, I find that students matched to resemble surveyed students along demographic and academic characteristics also do not respond to the signal (results not shown).

information to students one-on-one during the survey collection process. My findings suggest that if the interventions in these experiments were to be scaled through more common dissemination techniques such as brochures or websites, they might be unlikely to produce the same results. My conclusion is consistent with theories of limited attention in which individuals have "bandwidth constraints," and thus can only imperfectly integrate information—even readily accessible information—into their decision making.

There is evidence that surveys can increase the salience of existing information. Stango and Zinman (2011) found that credit card customers paid fewer penalty fees after participating in a survey, but only if the survey contained a question on penalty fees. Zwane et al. (2011) highlighted the connection between survey effects and inattention across multiple studies, showing that surveys can increase the salience of existing information. Thus, the survey and handout in this study likely made students notice and process the signal contained in the PSAT report. Effective information interventions must similarly take individuals' inattention into account in their design.

The results of this paper also have some immediate implications. First, the College Board should consider returning the AP Potential signal to PSAT paper reports. Second, it could increase the visual salience of the message by redesigning the report. Third, schools could work to provide a shock to attention at a potentially minimal cost. When distributing the reports, teachers could spend 15 minutes going over the information with their classes, as I did in this study. Teachers already receive training on the PSAT and are tasked with distributing the reports, so little additional training may be needed. A back-of-the-envelope calculation based on national data suggests that the additional cost of those 15 minutes would be approximately 40 cents per student.[32] More broadly, that a simple, binary signal derived from standardized test scores impacted student behavior suggests that existing performance data could be used more effectively to nudge individuals.

Caveats and areas for future work remain. Customized information interventions may be tricky to design if they inadvertently discourage those who do not meet some externally defined criterion. I find evidence that students near the margin who did not receive the signal were discouraged from taking AP classes, even though these students were of identical ability. On the other hand, noncustomized information (for example, providing data on the average returns to college) runs the risk of nudging individuals who are unlikely to receive a return. In the case of the AP Potential signal, the students nudged into the program performed just as well as other students, demonstrating the quality of the signal.

Though mismatch in AP course enrollments was reduced, many more students who do not meet any AP Potential criteria continued to enroll in AP. Given the high proportion of students who take AP but do not receive any college credit, overmatching may be a larger concern than undermatching, particularly in low-performing schools. However, if the benefits of overmatching

[32] This figure is calculated using national data on hourly mean wage and average class size for secondary teachers. A $38.51 hourly mean wage for secondary school teachers (excluding special and vocational education) was obtained from the Bureau of Labor Statistics' (2010) National Compensation Survey. An average class size of 24.2 for classrooms with departmentalized instruction is based on data from the National Center on Education Statistics' School and Staffing Survey (2012).

due to increased access to higher quality peers and teachers or other factors like better curricula outweigh the possible costs, these patterns may not be of as much concern. At the college level, Dillon and Smith (2013) found that students believe the benefits of attending a more selective college more than compensate for the possible costs of overmatch. Given the focus on increasing AP enrollment in low-performing districts like Oakland, this opinion is also shared by policymakers. Examining overmatching due to affirmative action, Bowen and Bok (1998) found no impact on degree completion. Further research on the effects of overmatching in both high school and college is needed.

Finally, although the AP Potential signal had a positive impact on the number of AP exams students passed, which offers a tangible benefit to students, it is unclear whether participating in AP coursework will bring students additional benefits. Future work will look for impacts on their college enrollment decisions. Given the prevalence of AP in high schools and the emphasis placed on AP coursework in college admissions, the lack of research on the causal effects of the AP program is a major gap in the education literature.

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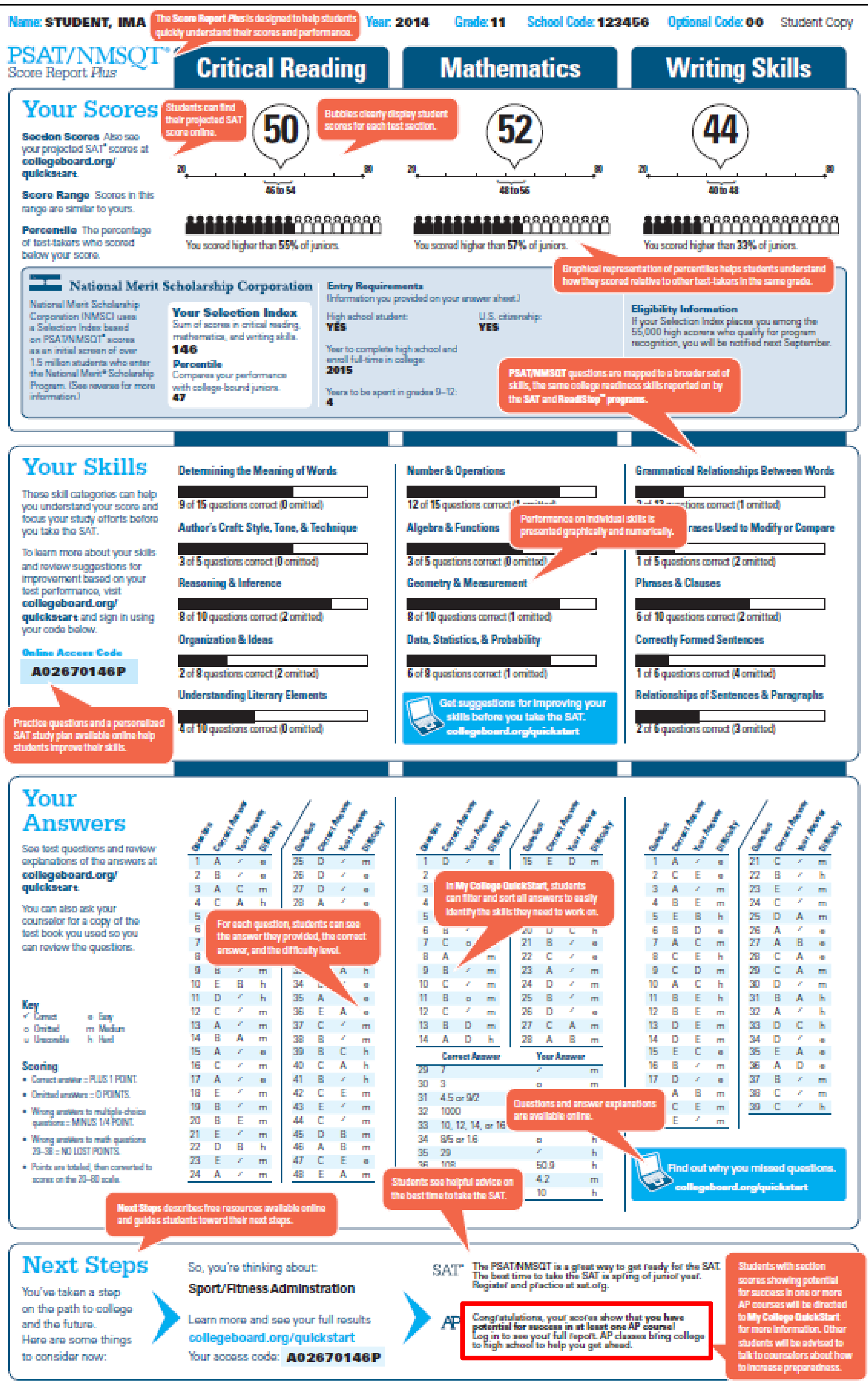
# APPENDIX A. ADDITIONAL TABLES AND FIGURES

## Table. A.1. AP Potential cut-point rules

| AP subject | Offered in Oakland | AP Potential rule | Correlation to exam passing | Share of Oakland students with AP Potential |
|---|---|---|---|---|
| Art History | | $R + W \geq 106$ | 0.563 | 0.100 |
| Biology | Y | $M + R \geq 114$ | 0.647 | 0.082 |
| Calculus AB | Y | $M \geq 60$ | 0.539 | 0.103 |
| Calculus BC | Y | $M \geq 56$ | 0.497 | 0.060 |
| Chemistry | Y | $\mathrm{R} + \mathrm{M} \geq 115$ | 0.611 | 0.078 |
| Chinese Language & Culture | Y | n/a | | |
| Comparative Gov't & Politics | | $R + M + W \geq 166$ | 0.598 | 0.084 |
| Computer Science | Y | $R + M \geq 114$ | 0.594 | 0.082 |
| English Language | Y | $R + W \geq 97$ | 0.762 | 0.153 |
| English Literature | Y | $R + W \geq 106$ | 0.754 | 0.100 |
| Environmental Science | Y | $R + M \geq 110$ | 0.668 | 0.101 |
| European History | | $R + M + W \geq 151$ | 0.604 | 0.132 |
| French Language & Culture | Y | n/a | | |
| Human Geography | | $R + M + W \geq 153$ | 0.644 | 0.123 |
| Macroeconomics | Y | $R + M \geq 116$ | 0.595 | 0.071 |
| Microeconomics | | $R + M \geq 111$ | 0.633 | 0.095 |
| Music Theory | | $W + M \geq 108$ | 0.536 | 0.089 |
| Physics B | Y | $R + M \geq 116$ | 0.583 | 0.071 |
| Physics C: Electricity & Magnetism | | $R + M \geq 122$ | 0.465 | 0.066 |
| Physics C: Mechanics | | $R + M \geq 117$ | 0.566 | 0.047 |
| Psychology | | $R + M + W \geq 145$ | 0.618 | 0.164 |
| Spanish Language | Y | n/a | | |
| Spanish Literature & Culture | Y | $R + W \geq 88$ | 0.409 | 0.223 |
| Statistics | Y | $R + M \geq 112$ | 0.651 | 0.090 |
| U.S. Gov't & Politics | Y | $R + M + W \geq 166$ | 0.648 | 0.084 |
| U.S. History | Y | $R + M + W \geq 157$ | 0.661 | 0.112 |
| World History | Y | $R + M \geq 104$ | 0.643 | 0.129 |

Note: AP Potential rules and correlations to exam passing are reported as in Zhang et al. (2014).

## Figure A.1. 2012 PSAT results report



## Figure A.2. Survey instrument

### PSAT AND BEYOND STUDENT SURVEY

*This survey is optional and is designed to find out how taking the PSAT may affect your opinion abour your academic ability and future academic plans. There are no right or wrong answers.*

*1. Please write your:*

First Name ______________ Last Name ______________

Grade ______________ Birth Date ______________

Student ID ______________

*2. Please rate yourself on each of the following as compared with the average student at your high school. For example, the average student at Oakland Tech has a 2.7 GPA. Mark your response with an X.*

*3. How confident are you of your answer?*

| | Highest 10% | Above Average | Average | Below Average | Lowest 10% | Practically Certain | Very Sure | Fairly Sure | Somewhat Sure | Not Sure At All |
|---|---|---|---|---|---|---|---|---|---|---|
| (SAMPLE) I think my height is... | | | | X | | | X | | | |
| I think my PSAT score will be... | | | | | | | | | | |
| I think my Academic Ability is... | | | | | | | | | | |
| I think my Math Ability is... | | | | | | | | | | |
| I think my Reading Ability is... | | | | | | | | | | |
| I think my Writing Ability is... | | | | | | | | | | |

*4. Looking ahead at the next 2-3 years, what are the chances that you will:*

| | Very Likely | Fairly Likely | Not Too Likely | Not At All Likely |
|---|---|---|---|---|
| Pass the CAHSEE | | | | |
| Take the SAT | | | | |
| Graduate high school | | | | |
| Attend community college | | | | |
| Attend a UC/CSU or other four-year college | | | | |

***5. Please write the number of Advanced Placement (AP) and Honors classes you plan on taking in the next year.***

How many Advanced Placement (AP) classes? ☐

How many Honors classes? ☐

*6. Looking ahead at the next 2-3 years, how much time do you plan on spending in a typical week doing the following:*

| | None | Less than 1 hour | 1-2 hours | 3-5 hours | 6-10 hours | 11-15 hours | 16-20 hours | Over 20 |
|---|---|---|---|---|---|---|---|---|
| Studying/homework | | | | | | | | |
| Socializing with friends | | | | | | | | |
| Exercise or sports | | | | | | | | |
| Working for pay | | | | | | | | |
| Volunteering | | | | | | | | |
| Watching TV | | | | | | | | |
| Household/childcare duties | | | | | | | | |
| Video/computer games | | | | | | | | |
| Reading for pleasure | | | | | | | | |
| Surfing the web or online social networks | | | | | | | | |

# Figure A.3. Survey informational handout

## PSAT 10th Grade Frequently Asked Questions

**Q: What AP classes should I take?**

Your PSAT results tell you whether you have high AP potential. You can log into My College QuickStart with the access code at the bottom of your PSAT results to find out which specific classes you have high potential for. The following is a list of the AP classes offered at Oakland Tech in Fall 2013. Talk to your counselor to find out more.

| | | | |
|---|---|---|---|
| AP American Government | AP Biology | AP Calculus AB | AP Chemistry |
| AP Chinese Language/Culture | AP Computer Science | AP English Literature | AP Environmental Sciences |
| AP Physics | AP Spanish Language | AP Statistics | AP U.S. History |

**Q: How can I use my PSAT scores to predict my SAT scores?**

The critical reading, mathematics, and writing skills multiple choice questions on the PSAT are the same kind as those in the SAT. The PSAT scale of 20 to 80 is comparable to the SAT scale of 200 to 800. However, there is no essay component in the PSAT.

| PSAT/NMSQT Score | SAT Critical Reading Range | SAT Math Range | SAT Writing Range | | PSAT/NMSQT Score | SAT Critical Reading Range | SAT Math Range | SAT Writing Range |
|---|---|---|---|---|---|---|---|---|
| 20 | 240-310 | 230-290 | 240-310 | | 51 | 490-560 | 490-560 | 490-570 |
| 21 | 240-320 | 230-300 | 250-320 | | 52 | 500-570 | 500-570 | 500-580 |
| 22 | 250-320 | 240-310 | 250-320 | | 53 | 510-580 | 510-580 | 510-590 |
| 23 | 250-330 | 250-320 | 260-330 | | 54 | 520-590 | 520-590 | 520-600 |
| 24 | 260-340 | 250-320 | 270-340 | | 55 | 530-600 | 530-600 | 530-610 |
| 25 | 270-350 | 260-330 | 270-350 | | 56 | 540-600 | 540-610 | 530-610 |
| 26 | 270-350 | 270-340 | 280-360 | | 57 | 550-610 | 550-620 | 540-620 |
| 27 | 280-360 | 270-350 | 290-370 | | 58 | 560-620 | 560-630 | 550-630 |
| 28 | 290-370 | 280-360 | 300-370 | | 59 | 560-630 | 570-630 | 560-640 |
| 29 | 300-380 | 290-370 | 310-380 | | 60 | 570-640 | 570-640 | 570-650 |
| 30 | 310-390 | 300-380 | 310-390 | | 61 | 580-650 | 580-650 | 580-650 |
| 31 | 310-390 | 310-390 | 320-400 | | 62 | 590-660 | 590-660 | 580-660 |
| 32 | 320-400 | 320-390 | 330-410 | | 63 | 600-670 | 600-670 | 590-670 |
| 33 | 330-410 | 330-400 | 340-420 | | 64 | 610-680 | 610-680 | 600-680 |
| 34 | 340-420 | 340-410 | 350-430 | | 65 | 620-690 | 620-690 | 610-690 |
| 35 | 350-430 | 350-420 | 360-430 | | 66 | 630-700 | 630-700 | 620-690 |
| 36 | 360-440 | 360-430 | 370-440 | | 67 | 640-710 | 640-710 | 620-700 |
| 37 | 370-440 | 360-440 | 370-450 | | 68 | 650-720 | 650-720 | 630-710 |
| 38 | 380-450 | 370-450 | 380-460 | | 69 | 660-720 | 660-730 | 640-720 |
| 39 | 380-460 | 380-460 | 390-470 | | 70 | 670-730 | 670-730 | 650-720 |
| 40 | 390-470 | 390-470 | 400-480 | | 71 | 680-740 | 680-740 | 650-720 |
| 41 | 400-480 | 400-470 | 410-490 | | 72 | 690-750 | 690-750 | 660-740 |
| 42 | 410-480 | 410-480 | 420-500 | | 73 | 700-760 | 700-760 | 670-740 |
| 43 | 420-490 | 420-450 | 430-500 | | 74 | 710-770 | 700-760 | 670-750 |
| 44 | 430-500 | 430-500 | 430-510 | | 75 | 720-770 | 710-770 | 680-750 |
| 45 | 440-510 | 440-510 | 440-520 | | 76 | 720-780 | 720-770 | 690-760 |
| 46 | 450-520 | 450-520 | 450-530 | | 77 | 740-780 | 730-780 | 690-760 |
| 47 | 460-530 | 460-530 | 460-540 | | 78 | 740-790 | 750-780 | 700-770 |
| 48 | 460-540 | 460-540 | 470-550 | | 79 | 750-790 | 740-790 | 710-770 |
| 49 | 470-540 | 470-550 | 480-560 | | 80 | 750-790 | 750-790 | 710-770 |
| 50 | 480-550 | 480-550 | 480-560 | | | | | |

## Figure A.3. (*continued*)

### PSAT 10th Grade Frequently Asked Questions

**Q: What colleges could I attend right now with my projected SAT score?**

The following tables show you the range of SAT scores of most of the students accepted at CSUs and UCs. If your score falls within the range (the 25% and 75%), you have a good chance of being accepted at that college. Remember you can always work to increase your SAT score and that other factors like the courses you take and your extracurricular activities can also improve your chances of admission.

| | California State University | | | | | |
|---|---|---|---|---|---|---|
| | Reading | | Math | | Writing | |
| | 25% | 75% | 25% | 75% | 25% | 75% |
| Bakersfield | 400 | 510 | 410 | 530 | N/A for admissions | |
| Cal Maritime | 460 | 580 | 500 | 600 | N/A for admissions | |
| Cal Poly Pomona | 460 | 580 | 490 | 630 | N/A for admissions | |
| Cal Poly San Luis Obispo | 540 | 640 | 580 | 680 | N/A for admissions | |
| Channel Islands | 440 | 540 | 430 | 540 | N/A for admissions | |
| Chico | 460 | 560 | 470 | 580 | N/A for admissions | |
| Dominguez Hills | 370 | 470 | 380 | 470 | N/A for admissions | |
| East Bay | 400 | 500 | 410 | 530 | N/A for admissions | |
| Fresno | 400 | 520 | 420 | 540 | N/A for admissions | |
| Fullerton | 440 | 540 | 450 | 570 | N/A for admissions | |
| Humboldt State | 460 | 580 | 450 | 570 | N/A for admissions | |
| Long Beach | 440 | 560 | 460 | 590 | N/A for admissions | |
| Los Angeles | 380 | 490 | 390 | 510 | N/A for admissions | |
| Monterey Bay | 420 | 540 | 420 | 540 | N/A for admissions | |
| Northridge | 400 | 520 | 410 | 530 | N/A for admissions | |
| Sacramento | 410 | 530 | 430 | 540 | N/A for admissions | |
| San Bernardino | 400 | 500 | 410 | 510 | N/A for admissions | |
| San Diego State | 480 | 580 | 500 | 610 | N/A for admissions | |
| San Francisco State | 440 | 560 | 450 | 570 | N/A for admissions | |
| San Jose State | 440 | 560 | 470 | 590 | N/A for admissions | |
| San Marcos | 430 | 530 | 440 | 550 | N/A for admissions | |
| Sonoma State | 465 | 560 | 460 | 570 | N/A for admissions | |
| Stanislaus | 400 | 510 | 410 | 530 | N/A for admissions | |

| | University of California | | | | | |
|---|---|---|---|---|---|---|
| | Reading | | Math | | Writing | |
| | 25% | 75% | 25% | 75% | 25% | 75% |
| Berkeley | 600 | 730 | 630 | 760 | 610 | 740 |
| Davis | 520 | 650 | 570 | 680 | 530 | 650 |
| Irvine | 510 | 620 | 560 | 680 | 520 | 640 |
| Los Angeles | 570 | 680 | 610 | 740 | 580 | 710 |
| Merced | 430 | 550 | 460 | 590 | 450 | 560 |
| Riverside | 450 | 560 | 480 | 610 | 460 | 570 |
| San Diego | 540 | 670 | 610 | 720 | 560 | 690 |
| Santa Barbara | 540 | 650 | 550 | 670 | 540 | 650 |
| Santa Cruz | 490 | 630 | 510 | 640 | 500 | 620 |

## Table. A.2. Heterogeneity in the revision of self-assessed academic ability

| DV: ∆Academic | (1) Standard Model | (2) By Prior | (3) By Performance | (4) By Ethnicity | (5) By Gender |
|---|---|---|---|---|---|
| Information Shock | 0.211*** (0.054) | 0.207** (0.083) | 0.187** (0.088) | 0.124 (0.102) | 0.229*** (0.067) |
| Shock X Above Avg. Prior | | -0.037 (0.101) | | | |
| Shock X Above Avg. on PSAT | | | 0.045 (0.105) | | |
| Shock X Black | | | | 0.150 (0.143) | |
| Shock X Latino | | | | 0.072 (0.149) | |
| Shock X Asian | | | | 0.113 (0.159) | |
| Shock X Female | | | | | -0.034 (0.099) |
| PSAT Score | 0.003* (0.002) | 0.007*** (0.002) | 0.002 (0.002) | 0.003* (0.002) | 0.003* (0.002) |
| Above Avg. Prior | | -0.549*** (0.082) | | | |
| Above Avg. on PSAT | | | 0.099 (0.129) | | |
| Demographic Controls | Y | Y | Y | Y | Y |
| $R^2$ | 0.109 | 0.224 | 0.111 | 0.113 | 0.096 |
| N | 312 | 312 | 312 | 312 | 312 |

"Above Avg. Prior" denotes that the individual initially rated his academic ability as above the school average. 'Above Avg. on PSAT' denotes that the individual scored above the school average on the PSAT.

*significant at 10%

** significant at 5%

*** significant at 1%.

## Table. A.3. Asymmetric revisions of self-assessments

| | (1) ∆Academic | (2) ∆Math | (3) ∆Reading | (4) ∆Writing |
|---|---|---|---|---|
| **Panel A** | | | | |
| Information Shock | 0.211*** | 0.199*** | 0.307*** | 0.205*** |
| | (0.054) | (0.052) | (0.076) | (0.067) |
| PSAT Score | 0.003* | 0.003* | 0.006*** | 0.008*** |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Demographic Controls | Y | Y | Y | Y |
| $R^2$ | 0.109 | 0.097 | 0.186 | 0.197 |
| **Panel B** | | | | |
| Positive Shock | 0.187** | 0.177* | 0.305** | 0.189 |
| | (0.084) | (0.098) | (0.146) | (0.123) |
| Negative Shock | -0.286*** | -0.293*** | -0.374*** | -0.257*** |
| | (0.091) | (0.097) | (0.100) | (0.094) |
| PSAT Score | 0.003* | 0.003* | 0.006*** | 0.008*** |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Demographic Controls | Y | Y | Y | Y |
| $R^2$ | 0.110 | 0.103 | 0.183 | 0.195 |
| N | 312 | 312 | 312 | 313 |

*significant at 10%
** significant at 5%
*** significant at 1%.

## Table. A.4. Self-confirmatory revisions of self-assessed academic ability

| | (1) All Students | (2) Low Ability Priors | (3) High Ability Priors |
|---|---|---|---|
| Positive Shock | 0.187** | 0.287** | 0.102 |
| | (0.084) | (0.135) | (0.094) |
| Negative Shock | -0.286*** | -0.208* | -0.308** |
| | (0.091) | (0.122) | (0.124) |
| PSAT Score | 0.003* | 0.006** | 0.007*** |
| | (0.002) | (0.002) | (0.002) |
| Demographic Controls | Y | Y | Y |
| $R^2$ | 0.110 | 0.135 | 0.266 |
| N | 312 | 140 | 172 |

*significant at 10%
** significant at 5%
*** significant at 1%.

## Table. A.5. Revisions of expected outcomes

| | (1) ΔAP | (2) ΔGradT est | (3) ΔT akeSAT | (4) ΔGradHS | (5) ΔCommColl | (6) Δ4YrColl |
|---|---|---|---|---|---|---|
| **Panel A** | | | | | | |
| Information Shock | 0.118** | 0.068 | 0.026 | 0.026 | -0.042 | 0.094** |
| | (0.059) | (0.042) | (0.047) | (0.026) | (0.071) | (0.047) |
| PSAT Score | 0.004** | 0.000 | -0.001 | 0.001 | 0.002 | 0.001 |
| | (0.002) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Demographic Controls | Y | Y | Y | Y | Y | Y |
| $R^2$ | 0.050 | 0.042 | 0.031 | 0.020 | 0.014 | 0.038 |
| **Panel B** | | | | | | |
| Positive Shock | 0.268** | -0.094 | -0.038 | 0.032 | -0.047 | 0.135* |
| | (0.129) | (0.074) | (0.067) | (0.038) | (0.115) | (0.080) |
| Negative Shock | -0.024 | -0.222*** | -0.105 | -0.033 | 0.044 | -0.116 |
| | (0.125) | (0.079) | (0.086) | (0.056) | (0.110) | (0.078) |
| PSAT Score | 0.004** | 0.000 | -0.001 | 0.001 | 0.002 | 0.001 |
| | (0.002) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Demographic Controls | Y | Y | Y | Y | Y | Y |
| $R^2$ | 0.056 | 0.064 | 0.037 | 0.021 | 0.014 | 0.044 |
| N | 259 | 304 | 312 | 307 | 304 | 313 |

*significant at 10%

** significant at 5%

*** significant at 1%.

## Table. A.6. Summary statistics for comparison groups

| | (1) 2013 | (2) 2011/2012 | (3) Surveyed students | (4) Matched students |
|---|---|---|---|---|
| Black | 0.373 | 0.398 | 0.335 | 0.342 |
| Latino | 0.214 | 0.183 | 0.214 | 0.182 |
| Asian | 0.147 | 0.169 | 0.162 | 0.199 |
| White | 0.221 | 0.208 | 0.241 | 0.232 |
| Female | 0.509 | 0.484 | 0.549 | 0.493* |
| Eligible for F/R lunch | 0.488 | 0.477 | 0.487 | 0.486 |
| English learner | 0.089 | 0.094 | 0.071 | 0.085 |
| Proficient/advanced in math | 0.345 | 0.370 | 0.375 | 0.397 |
| Proficient/advanced in English | 0.648 | 0.552*** | 0.704 | 0.598*** |
| GPA above 3.0 | 0.394 | 0.430 | 0.434 | 0.480 |
| Took PSAT | 0.904 | 0.843*** | 1.000 | 1.000 |
| Test-takers with AP Potential | 0.415 | 0.395 | 0.446 | 0.405 |
| Number of AP courses offered | 15 | 15 | | |
| N | 584 | 1089 | 439 | 856 |

* significantly different at the 0.10 level, two-tailed test.

*** significantly different at the 0.01 level, two-tailed test.

**Figure A.1. Relationship between non–outcome variables and R**

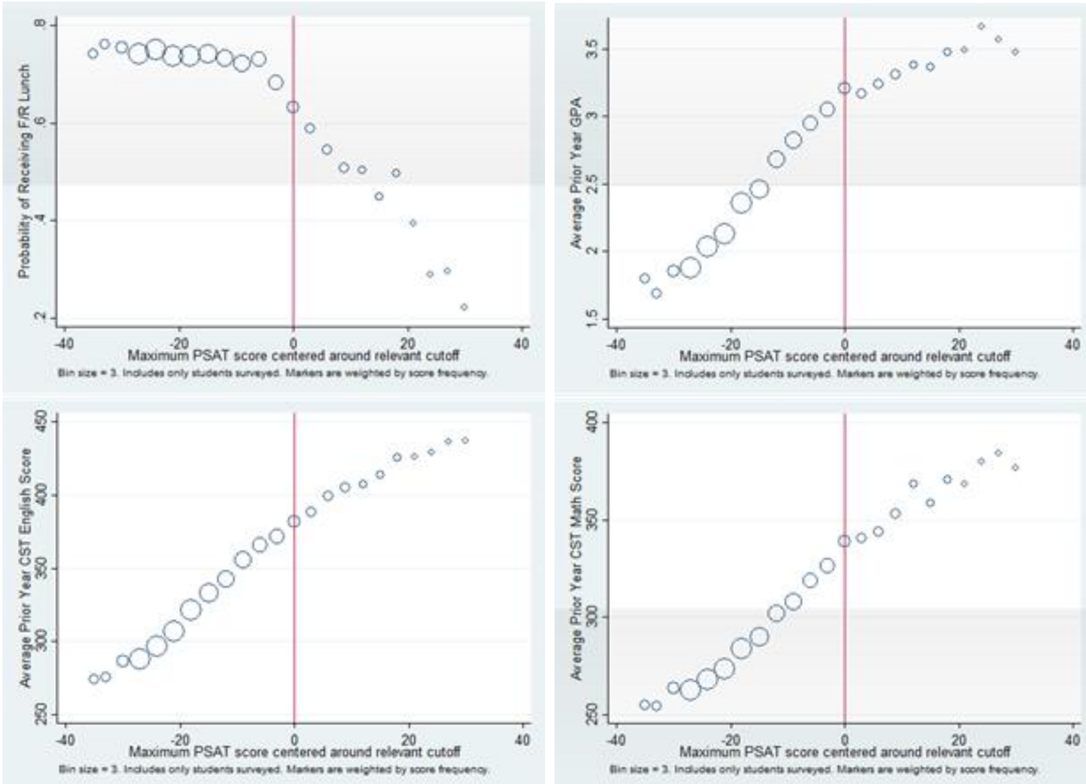



**Figure A.2. Relationship between the probability of participating in the survey and R**

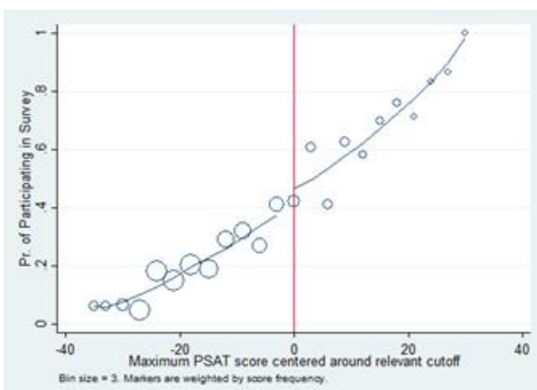
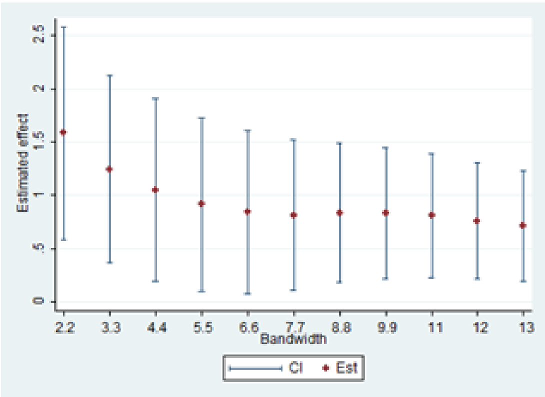
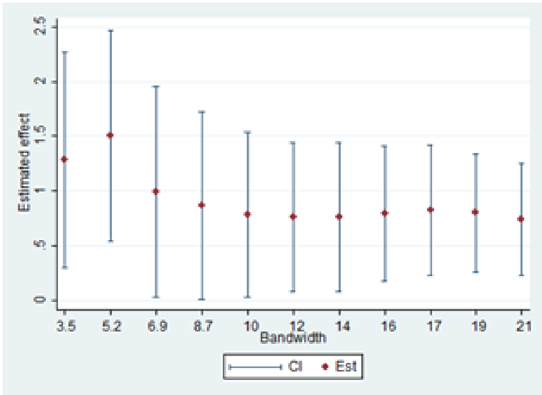


**Figure A.3. Relationship between bandwidth and nonparametric estimates on surveyed students**

**Local linear estimates using a triangle kernel**




**Local linear estimates using a rectangle kernel**

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