Information Shocks about Ability and the Decision to Enroll in Advanced Placement: Evidence from the PSAT

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Abstract

This study asks whether lack of information about ability helps explain why high-performing students from disadvantaged backgrounds tend to under-invest in their education. I examine an individualized signal of aptitude for Advanced Placement known as "AP Potential" that is provided in PSAT reports. By collecting high-frequency panel data on subjective beliefs from students in Oakland, California, I show that the "AP Potential" signal has informational value: students with the same scores and prior beliefs who receive the signal experience larger information shocks. These shocks lead students to revise their beliefs about their ability, the number of AP classes they plan to take, and the likelihood that they will attend a four-year college, consistent with a Bayesian updating model. I then exploit the deterministic relationship between test scores and the AP Potential signal in a Regression Discontinuity (RD) design and find that receiving the signal caused surveyed students at the margin to enroll in approximately one more AP class the following semester. This effect amounts to raising the number of high-ability students in college-level courses and reducing mismatch in course enrollments. The results suggest that providing a credible, individualized signal of ability is a cost-effective means of increasing human capital investments among disadvantaged students.

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1 Introduction

The majority of high-performing students from disadvantaged backgrounds do not apply to selective colleges, even though doing so would benefit them academically and financially (Hoxby and Avery, 2012). One leading hypothesis for this puzzling phenomenon is that these students lack information. In the face of uncertainty about the costs and returns to human capital investments as well as their individual tastes and abilities, individuals form expectations and make human capital investment decisions using the information available. Researchers have begun testing the information gap hypothesis through randomized control trials of "information interventions." For example, Oreoupoulos and Dunn (2012) find that disadvantaged students exposed to messages about the benefits of post-secondary education report higher likelihoods of completing a college degree, and Hoxby and Turner (2013) find that providing semi-customized information about college costs leads high-achieving, low-income students to apply to and enroll in more selective colleges.

These studies show that uncertainty about costs and benefits makes up a piece of the puzzle. Another possible, non-rival theory is that high-performing disadvantaged students are uncertain of their individual level of ability. This hypothesis has been suggested in studies of mismatch between student ability and college quality. Hoxby and Avery (2012) note that high-performing, low-income students who do not apply to selective schools are likely to lack information and encouragement that their counterparts who do apply to selective colleges receive since the latter tend to be exposed to a critical mass of high-achieving students and teachers while in high school. Dillon and Smith (2013) also posit that disadvantaged students' college application decisions can be explained in part by incomplete information about how their abilities compare with other college applicants. Using a proxy for access to this information, they find that better informed students are less likely to undermatch.

Motivated by these findings, this paper studies how receiving individualized information about ability impacts human capital investment in high school, a pivotal time in which course-taking and academic effort decisions are made that affect students' college choice set. Using administrative and survey data from Oakland public schools, I explore how receipt of new information about ability transmitted by the Preliminary SAT (PSAT) affects students' beliefs about their ability, expectations of future academic outcomes, and decision to enroll in Advanced Placement (AP) courses, a key step on the path to admission into selective four-year colleges (Geiser and Santelices, 2006). To the best of my knowledge, this is the first study to identify the causal effect of providing a signal of ability. I find that providing credible, individualized information about ability is a cost-effective means for increasing human capital investments among high-performing, disadvantaged students.

This study builds on a growing body of work on the effects of learning about own ability. Goodman (2012) shows that a mandate that made the ACT compulsory for high school juniors led to an increase in the enrollment of students from lower socioeconomic backgrounds in more selective colleges and interprets this finding as being reflective of many high-ability students from disadvantaged backgrounds underestimating their ability. If disadvantaged students across the distribution of ability lack information, it follows that many may also overestimate their ability. Jacob and Wilder (2010) find that socioeconomically disadvantaged students start out with very high expectations about the likelihood that they will attend college but lower them during high school as they observe changes in their GPA. In a similar vein, Fryer and Holden (2012) observe that the academic performance of lower-performing students suffered following an experiment that incentivized them to take practice math tests. The authors argue that this result is most likely explained by students learning that their own ability was lower than they believed.

While these studies suggest information about own ability can affect students' educational decisions and performance (in both positive and negative ways), they assume that students derived new information about their ability from their GPA or the assessments they were induced to take. However, a particular behavior may be consistent with multiple characterizations of both expectations and preferences, making it difficult to ascertain that a change in beliefs about ability in fact occurred. Furthermore, in the absence of baseline data on expectations, one could easily confuse positive information for negative information when a student's performance is high yet happens to be lower than what he had anticipated, and vice versa. Even when accounting for observable information available to the student, as Fryer and Holden (2012) do, there could be unobservable factors that would have led the student to make a valuation of his expected performance different than the researcher.

In response to this identification issue, economists have begun eliciting self-reported subjective beliefs using surveys in order to back out new information from changes in beliefs. Stinebrickner and Stinebrickner (2012) link longitudinal surveys to administrative data from undergraduates at Berea College to explore how students update expectations about future academic performance in response to new information from grades. They conclude that dropout rates between the first and second years of college would be significantly reduced if no learning about own ability occurred. Zafar (2011) similarly shows that students update their expectations in response to new information received from college grades using longitudinal survey data from undergraduates at Northwestern University. He finds that this learning plays a role in the decision to switch majors.

A challenge to this approach is that the source of the new information cannot be pinned down. Zafar (2011) and Stinebrickner and Stinebrickner (2012) both attribute information shocks solely to college GPA but cannot rule out other sources. To address the question of whether individuals respond to a well-identified source of information, the researcher must elicit very high-frequency survey data about expectations, observe the innovation in the individual's information set, and link expectations to outcomes. Due to these difficulties, no previous work has been able to determine the causal effect of a particular information intervention on expectations and realized outcomes.

In this paper, I focus on a specific information signal known as "AP Potential," which the College Board began providing students via the PSAT in 2013, and whether it contains new information about own ability that is effective in leading high-ability students in Oakland to enroll in AP courses. I begin by surveying students about their expected performance on the PSAT, their beliefs about their abilities, and their expectations about future academic outcomes before and after distributing their PSAT results reports. This data allows me to identify the information shock received from the PSAT as the difference between students' prior and posterior beliefs about their performance. I establish that although the PSAT is, on average, a negative information shock, the AP Potential signal itself contains new information for high-ability students: students with the same PSAT score and prior beliefs about own ability who receive the AP Potential signal experience a more positive information shock. The information shock in turn leads students to revise their beliefs about their ability and their expectations of a subset of future academic outcomes, particularly the number of AP classes they plan to take, in a manner consistent with Bayesian updating.

Although the PSAT and AP Potential signal contain new information that leads students to revise their beliefs about own ability and future course-taking plans, it is possible that stated beliefs do not reflect future actions. For this reason, I focus next on estimating whether the AP Potential signal has a causal effect on the number of AP classes in which students actually enroll by exploiting the deterministic relationship between PSAT scores and the AP Potential signal in a Regression Discontinuity (RD) design. Both graphical and more formal parametric and non-parametric methods robustly demonstrate that receiving the AP Potential signal caused surveyed students at the margin to enroll in approximately one more AP class the following academic year. Given the fact that students to the left of the AP Potential cut-point had very low rates of AP participation, this effect amounts to increasing the number of high-ability students taking college-level courses.

When I extend this analysis to students in other schools who did not take the survey, I find that the AP Potential signal had no effect on their course enrollment decisions. This result is not altogether surprising since students who participated in the survey were not just handed back their PSAT results report, but were also given additional information to help them interpret each section of the report. Following a brief explanation of the results report and the AP Potential message, surveyed students received a handout that listed the AP courses offered at their high school, a table to predict their SAT scores using their PSAT scores, and the SAT score ranges of students admitted to California's four-year colleges. The most likely explanation for why a treatment effect was only detected for surveyed students is that the additional information they received intensified the signal's underlying effect. This additional intervention would be straightforward and inexpensive to replicate.

Increasing AP enrollment among minority and low-income students is a well-publicized and well-funded goal of education policymakers. [1] In addition, the same mechanisms that induced high-ability, disadvantaged students to enroll in AP could apply to other human capital investment decisions that policymakers seek to influence. The results from this paper suggest that well-designed information interventions may be one of the most cost-effective methods to achieve these goals. Unfortunately, not enough time has elapsed since students were provided the AP Potential signal for the first time to study additional outcomes like performance in AP exams and college enrollment. Although participating in AP increases access to high-achieving peers and teachers, provides an opportunity to earn college credit, and plays an important role in the admissions decisions of selective colleges, future work will further explore how students were impacted.

The next section describes the details of the PSAT and AP Potential signal. Section 3 outlines a Bayesian learning framework to illustrate how new information about own ability can affect students' formation of expectations, and ultimately, educational decision-making. Section 4 describes the administrative and survey data from the Oakland school district used in the study. In Section 5 I analyze the survey data to determine whether the PSAT and AP Potential signal contain new information and whether students use this information to update their beliefs about own ability and expectations of future outcomes in a manner consistent with the Bayesian framework outlined in Section 3. Having established the informational value of the AP Potential signal, Section 6 focuses on identifying its causal effect on the number of AP courses students enroll in using an RD design. Section 7 discusses the results and outlines future work.

2 Background

There is a long history in education of using standardized testing as a means to communicate information to students, traceable back to the work of Novick (1970) and Novick and Jackson

[1] Several states have pushed to expand AP programs, particularly for disadvantaged students (Lerner and Brand, 2008). These efforts have been supported by federal, state, and private funds. As one example, the U.S. Department of Education allocated more than $273M between 2001 and 2011 to Advanced Placement Incentive Program Grants to increase participation of low-income students in AP courses and tests (U.S. Department of Education, 2014).

(1970).[2]. Novick (1970) wrote of the possibility that an assessment could provide a student with "information about himself" to make better educational decisions. Novick and Jackson (1970) furthered this work, writing that information provided by testing could "encourage potentially qualified students, whose backgrounds have not given them expectations of college attendance." Although standardized testing is not the only way to measure and provide information about ability, it is reliable and scalable.

Today, educational organizations and testing companies continue the claim that assessment results can provide valuable information to students. One example is the PSAT, which provides information about students' aptitude for Advanced Placement (AP), a national program that offers college-level courses and exams in high school. Students typically take AP courses, which are taught by specially-trained teachers in the AP curriculum for their subject, during their junior and senior years of high school. Students who take AP courses also take corresponding exams administered by the College Board. AP exam scores range from 1 to 5, and a score of 3 or above is considered passing and generally qualifies students to receive college credit. For example, the University of California system grants credit for all subjects on which students score 3 or higher. Figure 1 shows a timeline of events related to the PSAT, AP program, and college.

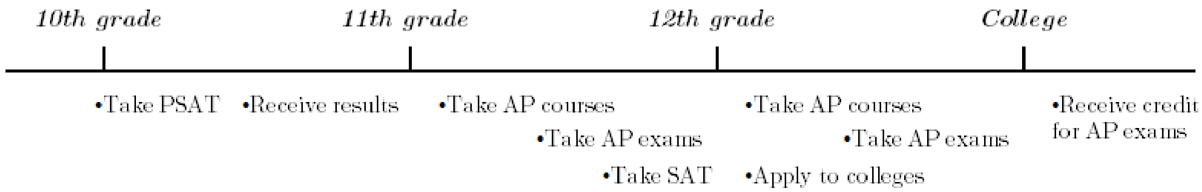
The College Board administers the PSAT, a shorter version of the SAT, to over three million 10th and 11th graders nationwide each year. The College Board developed the AP Potential signal based on research by Camara and Millsap (1998), which showed that PSAT scores are strongly correlated with performance on most AP exams. Further, the correlations between PSAT scores and AP exam scores are much stronger than those between AP exam scores and high school GPA or grades in prior relevant courses.[3] Researchers selected the measure with the highest correlation to performance on each AP exam from among seven PSAT scores: verbal (V), mathematics (M), writing (W), $V + M$, $V + W$, $M + W$, and $V + M + W$.[4] The selected PSAT scale was divided into 5-point or 10-point score ranges, and for each score range, the percentage of test-takers earning a score of 3 or better was calculated. A binary AP Potential signal for each AP subject was thus defined using the cut-point score that corresponded to passing that AP exam with at least a 60% probability. Table A.1 in the Appendix shows the scores and cutoffs used to define AP Potential for each AP subject.

[2]Novick was a consultant for the Educational Testing Service and the American College Testing Program and went on to pen the 1985 Standards for Educational and Psychological Testing

[3]All but four AP subject exams (in foreign languages and studio art) exhibited a correlation of 0.40 or higher with one or more scores, and in the majority of the cases the correlations were above 0.50.

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

Figure 1: Typical Path to a Selective College



In addition to the AP Potential signal it provides, the College Board claims in its promotional materials that the PSAT itself is an early source of new information about college readiness for students, as it provides a good estimate of future SAT performance as well as a comparison to students around the country. Though the PSAT was originally designed as an optional test for 11th graders, many school districts now require students to take the PSAT, and to take it earlier (some as early as 9th grade), precisely for the information it may provide to students at a critical point in their high school careers.[5] Based on this belief, the Oakland Unified School District (OUSD) began offering the PSAT to 10th graders at no cost in 2006. The expectation was that 100% of 10th graders would participate, but actual participation rates were much lower.[6] In 2011, upon receipt of a $3M, four-year Investing in Innovation (i3) grant from the U.S. Department of Education, the district partnered with the College Board and made 100% participation in the PSAT a priority. Since then, 10th grade participation in the PSAT rose from 39% to 74% 2013, a 90% increase.

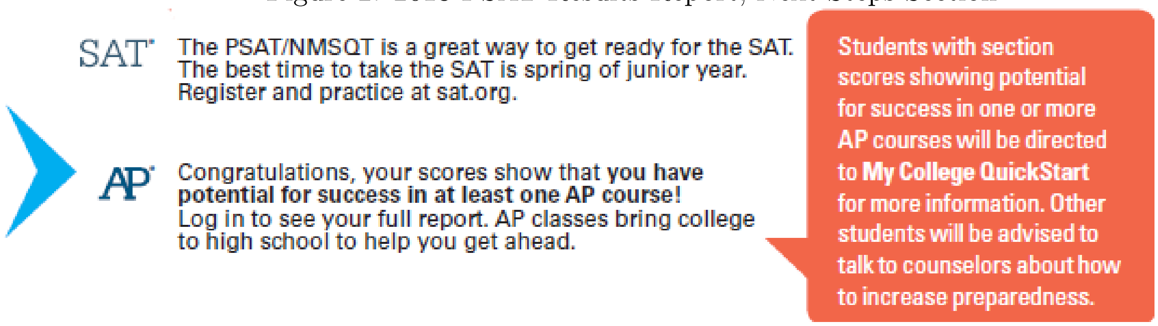
The AP Potential program was first rolled out in 2000, when the College Board began providing schools with a roster of students that met the criteria outlined above. In 2004, an online tool was introduced that allowed schools to select the default probability of passing (for example, 50% instead of 60%) in order to help schools decide which AP courses to offer and which students to recruit into AP classes. Information was always provided on a course-by-course basis (that is, a list of students was provided for each AP subject). Students were not informed of their AP Potential status. In 2012, the College Board added AP Potential results, still at the course level, to My College QuickStart, a website where students can review their PSAT scores and other College Board services. In Oakland, the AP Potential online tool for schools and the My College QuickStart website for students are

[5]Another incentive to take the PSAT is that scores are used as an initial screening tool for the National Merit Scholarship Program. However, only students who take the test in 11th grade are eligible to compete.

[6]Ninth and 11th graders can also take the test, though they are not required to and are not eligible to take it free of cost unless their schools apply for a waiver from the $14 fee.

both unpopular. Usage rates of My College QuickStart among Oakland students range between 10 and 15%,and it is unclear if all students who log in navigate to the AP Potential part of the website. Use of the AP Potential online tool for schools is similarly low. Each year, only one or two out of 14 high schools in Oakland access the AP Potential online tool (College Board, 2014).

Figure 2: 2013 PSAT Results Report, Next Steps Section



Possibly in response to these low rates of take-up, in 2013 the College Board added a message about AP Potential to the PSAT paper results that every student receives. Figure A.1 in the Appendix shows a sample results report from 2012. Between 2012 and 2013, the "Next Steps" section at the bottom of the report was redesigned. As Figure 2 shows, beginning in 2013 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 based on whether they met at least one of the AP Potential criteria listed in Table A.1 in the Appendix. This change achieved three things: first, it converted the information into a more salient signal–either students had AP Potential or they didn't; second, it made students, not school administrators, the main recipients of the information; and third, it removed barriers to accessing the information.

An underlying motivation for creating these types of designations using standardized testing is the well-established fact that GPA is a noisy predictor of success in college for minority students (e.g. Thomas and Stanley, 1969; Dalton, 1974; and Zwick and Sklar, 2005). As the fitted scatter plots in Figure A.2 in the Appendix show, this is very much true for students in Oakland. Whereas GPA is noisy, PSAT scores are a strong predictor SAT performance, an important academic measure for high school students. Furthermore, the strength of the relationship between grades and SAT performance is weaker for minority students. Therefore, the information value of signals like AP Potential is potentially higher for groups of interest to policymakers. As the following quote from a counselor at Oakland High School suggests, students themselves become aware of the conflicting information they receive from the PSAT versus grades: “It’s frustrating, because some of these kids are getting As and Bs in their classes but then get really low PSAT scores [...] and they come to me, upset and confused.”

3 Theoretical Framework

Individuals make educational choices like whether to enroll in AP or which colleges to apply to based on their beliefs about the returns and costs of these decisions. To illustrate, consider a simple one-factor model of selection into AP. Students who participate in the college track by enrolling in programs like AP obtain the following return:

$$r_{AP}(\alpha_i) = \delta_0 + \delta_1 \alpha_i - c,$$

where $\delta_0 > 0$ and $\delta_1 > 0$, such that δ_0 is the main return to participating in AP, which applies irrespective of the individual’s ability, and δ_1, such that the program yields a higher return to more able students, ensuring that high-ability individuals are positively selected, which we know empirically to be the case. Because students must exert more effort if they participate in AP, there is a cost c associated with the program, which for simplicity we can assume is fixed. The details of this expression matter only to illustrate that students must at a minimum be well-informed about their ability and the returns and costs to the educational decision they are considering. Thus, under complete information, it is optimal to participate in AP if the following condition is met:

$$\alpha_i \geq \frac{c - \delta_0}{\delta_1} \tag{1}$$

In more general terms, a student’s ability must cross some threshold that is increasing in the costs and decrease in the returns to a particular human capital investment. That individuals are uncertainty about the costs and benefits of educational investments is supported by past research (e.g. Jensen (2010), Dynarski and Scott-Clayton (2006), Oreopoulos and Dunn (2012), and Hoxby and Turner (2013)). However, it is also possible that a student’s true ability is unknown to her, particularly if she does not have access to high-ability peers, teachers, and family members as sources of information. Information constraints about ability among disadvantaged students have been discussed in past work by Jacob and Wilder (2010), Hoxby and Avery (2012), and Dillon and Smith (2013).

Therefore, consider the case in which individuals are distinguished by unobserved ability. In this case, the AP enrollment decision will depend on her best estimate of α_i using the information available to her. 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 and teachers are. This self-assessment reflects her true ability with an added error term:

$$s_i = \alpha_i + \epsilon_i^s,$$

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

One possible framework for understanding how information that reduces students' uncertainty can affect educational choices is a rational Bayesian learning model in which individuals update beliefs based on new information and its relative precision. Individuals are assumed to use all available information in forming expectations; therefore, revisions of expectations are determined solely by new information. I further assume that, at time $t+1$, the individual has access to all information that was available at time t. Consider the case in which a new signal of ability such as the PSAT becomes available at time $t+1$, where:

$$PSAT_i = \alpha_i + \epsilon_i^{PSAT},$$

$\epsilon_i^{PSAT} \sim N(0, \sigma_{PSAT}^2)$ and hence the signal has precision $\rho^{PSAT} = \frac{1}{\sigma_{PSAT}^2}$. The precision of both the prior 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 to the individual, $I_{i,t+1}$, which can be expressed as follows:

$$I_{i,t+1} = PSAT_i - E(PSAT_i|\Omega_{i,t}), \tag{2}$$

where $\Omega_{i,t}$ denotes the information set available to the individual at time t and $E(I_{i,t+1}|\Omega_{i,t}) = 0$. Because the signal was not able to be predicted 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.[7] When the new signal becomes available, the student uses the information content to update her expected ability thusly:

$$E(\alpha_i|\Omega_{i,t+1}) = \gamma^s s_i + \gamma^I I_{i,t+1}, \tag{3}$$

[7] In reality, individuals select into receiving the PSAT signal at time $t+1$. Therefore, we will observe PSAT scores only for individuals with $E(PSAT_i|E(\alpha_i|\Omega^1) > \bar{\alpha})$ in the absence of a mandate, where $\bar{\alpha}$ is a threshold increasing in the costs of the test, and decreasing in its value. However, revisions in individuals' expected ability and decision to enroll in AP are based on the information shock (that is, the deviation from the prior expectation) rather than the absolute level of performance on the PSAT.

where $\gamma^s = \frac{\rho^s}{\rho^s+\rho^{PSAT}} \in [0,1]$ is the weight assigned to the individual's 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.

When only the student's self-assessment is available to her, she will decide to enroll in AP if the following condition is met:

$$E(\alpha_i|\Omega_{i,t}) = s_i \geq \frac{c-\delta_0}{\delta_1} \tag{4}$$

The decision to enroll at time $t+1$, however, utilizes the new information as follows:

$$E(\alpha_i|\Omega_{i,t+1}) = \gamma^s s_i + \gamma^I I_{i,t+1} \geq \frac{c-\delta_0}{\delta_1}, \tag{5}$$

This simple Bayesian framework has several implications. 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 $\rho^{PSAT} > \rho^s$ for disadvantaged students given the noisy and incomplete nature of their prior sources of information about ability and the fact that the PSAT is designed as a nationally standardized measure of college aptitude. The magnitude of the revision students make depends on the relative precision of the information shock and the 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, they may also revise their AP enrollment decision if the change in their expected ability is large enough to alter the result of equation 4 versus equation 5. If the student receives a large enough positive shock, she revises her expected ability and the likelihood of participating in AP increases. Although policymakers cannot control the size of the information shock provided by a given intervention, they can control the precision by providing a credible, meaningful, and salient signal. Finally, note that the chances of enrolling in AP under uncertainty may be lower or higher than the optimal decision based on full information, although having access to the PSAT signal should reduce error.

4 Data

4.1 Administrative Data

The data for this paper were provided by the Oakland Unified School District, a public school district in northern California with an enrollment of approximately 47,000 students during the 2013-14 school year. The Oakland Unified School District resembles other medium-sized urban school districts around the country like St. Louis, Baltimore, Cleveland, Atlanta, and Washington D.C., with a high share of minority, socioeconomically disadvantaged students and poor academic results. Academically, Oakland students score in the 28th percentile in math and 25th percentile in reading compared to the rest of the nation (Global Report Card, 2011).

The data span all high school students enrolled in non-charter 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. [8] Students are tracked longitudinally across years. The data consist of administrative data on student demographics, course enrollment and grades, and graduation; standardized test results from the California Department of Education and the College Board; and postsecondary enrollment from the National Student Clearinghouse, a non-profit organization that provides degree and enrollment verification for more than 3,300 colleges.

Table 1 lists descriptive statistics for the overall sample of high school students, as well as by ethnicity. Among students in grades 9-12, 38.0% are black, 32.2% are Latino, 20.1% are Asian, and 5.84% are white.[9] Less than half of parents completed high school or better, and about two-thirds of students are eligible for free or reduced-price lunch. A large share of Latino students (39.9%) and Asian students (23.9%) are English language learners and are born outside of the U.S. Academically, Table 1 shows low performance levels overall, as well as large achievement gaps between ethnic groups, along almost every outcome. For example, district-wide, only 19.4% of students in grades 9-12 score proficient or advanced on the California Standards Test in English, with white students almost five times more likely to score in these passing ranges than black students.

As might be expected given the small share of white students in the district, there is evidence of substantial academic tracking by ethnicity. Almost two-thirds of white students enroll in an AP course in grade 12, compared to one-sixth of black students. Even among students who do participate in AP, gaps in achievement persist. Only 16.6% of black students who take at least one AP test pass and become eligible to receive college credit, compared to 79.9% of white students. A comparison of the share of students who meet the AP Potential criteria and the share of students who participate in AP courses suggests that more black, Latino, and Asian students enroll in AP courses than have AP Potential. However, not shown in Table 1 is the relationship between AP Potential status and AP course enrollment. More than a third of black students with AP Potential never take an AP course, yet 75% of black students who take AP courses do not meet any of the AP Potential criteria, suggesting that there are in fact highly qualified minority students who are

[8] All years refer to academic years henceforth.

[9] The city of Oakland's population was 28.0% black, 25.9% white, 25.4% Latino, and 16.8% Asian as of the 2010 census.

passed by for AP, but also that less qualified minority students are being recruited instead. Although there are other factors like student interest and motivation that should determine enrollment in AP courses, in the presence of space constraints these comparisons imply that schools and students are not effectively utilizing information about ability as a primary factor.

Table 1: Summary Statistics of Oakland HS Students

	(1) All Students	(2) Black	(3) Latino	(4) Asian	(5) White
Black	0.380				
Latino	0.322				
Asian	0.201				
White	0.058				
Female	0.507	0.526	0.495	0.499	0.497
Parent Ed: HS Grad or Better	0.484	0.580	0.307	0.498	0.789
Eligible for F/R Lunch	0.680	0.663	0.758	0.764	0.236
English Learner	0.193	0.011	0.399	0.239	0.054
Foreign Born	0.237	0.070	0.407	0.318	0.078
GPA	2.432	2.069	2.257	3.055	3.230
	(1.015)	(0.904)	(0.968)	(0.880)	(0.845)
Prof/Adv in English	0.194	0.115	0.148	0.319	0.545
Prof/Adv in Math	0.129	0.086	0.113	0.215	0.217
Took PSAT Grade 10	0.633	0.554	0.638	0.725	0.818
Took PSAT Grade 11	0.251	0.175	0.260	0.347	0.330
PSAT Test-Takers with AP Potential	0.237	0.109	0.0656	0.334	0.763
Took AP Class Grade 11	0.233	0.137	0.182	0.408	0.551
Took AP Class Grade 12	0.291	0.167	0.214	0.532	0.645
AP Test-Takers that Passed	0.424	0.166	0.450	0.389	0.799
Graduated Grade 12	0.676	0.612	0.616	0.817	0.870
HS Grads Enrolled in 4-yr College	0.295	0.245	0.201	0.423	0.584
N	44222	16809	14245	8907	2581

4.2 Survey Data

To better understand how receiving information affects students' beliefs, I gather survey data from 10th grade students who took the PSAT in October 2013 at Oakland Technical High School, Oakland's largest secondary school. Oakland Tech, as the school is known locally, is located in a middle-class neighborhood in Oakland, but 70% of the school's students live outside of the neighborhood. Its student population is about 2100 students, which is 37% black, 22% white, 19% Asian, and 18% Latino. It is widely considered to be the best traditional public high school in Oakland but exhibits large achievement gaps between ethnic groups: 93% of white students graduate, compared to 78% of black students. The school is known for having very distinct academic tracks, with students separated into "academies" with differing course offerings and levels of rigor. One teacher at the school described the school thusly: "[Oakland Tech] is two schools within one school. It's the most segregated school in Oakland."

The survey instrument (see Figure A.3 in the Appendix) was designed with the theoretical framework outlined in Section 3 in mind and the school was selected based on its size and the willingness of school administrators to participate in the study.[10] The survey is divided into three parts. The first part focuses on students' self-assessments, beginning with their expected performance on the PSAT. This question is used to measure the information shock received. I also ask students to report their confidence in their responses in order to test whether students update in a manner consistent with the rational learning model described in Section 3. Part 2 of the survey asks students to state their expected academic outcomes to measure whether students revise their expectations when they receive new information. Part 3 asks about planned time expenditures. This question was intended to measure expected academic effort and to provide data on students' tastes for academic versus non-academic activities. However, many students left this section either partially or completely blank, so I ignore this question in the analysis that follows.

Unlike Zafar (2011), who elicits beliefs in terms of probabilities, I provide students with categorical ranges. Rather than ask students for their expected percentile ranking on the PSAT, I ask them to select one of five categories, ranging from "Highest 10%" to "Lowest 10%," and rather than ask students to state the probability that they will attend a four-year college, I ask them to select one of four options, ranging from "Not at all likely" to "Very likely." In the case of AP course enrollment, I ask for the explicit number of courses the student plans to take. Oakland educators who provided feedback on the survey instrument agreed that percentiles and probabilities were not adequate concepts to include in the survey. Note that students were asked to rate their performance and own ability relative to other students at the same high school. Wording the survey this way reduces measurement error and simplifies the questions for students.

I surveyed students in their English classes over the span of four weeks, between mid-January 2014 and mid-February 2014. Eliciting subjective evaluations of self-ability just before and after students receive their PSAT scores allows me to measure the value of the information shock received

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

Table 2: Comparing Survey Participants to the 10th Grade Population

	(1)	(2)	(3)
	All 10th Graders	Took PSAT	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	527	337

by each student that is attributable solely to the PSAT. 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 for all the four-year public colleges in California, and a list of the AP courses offered at the school (see Figure A.4 in the Appendix). Next, I briefly explained the report and handout to students, following the same script. I first showed students where they could find their scores, how to interpret the percentiles, and how to use the handout. I then asked students to check whether they had received the AP Potential message, pointing out the list of AP courses in the handout. Finally, I told students they could log into My College QuickStart for more information. Students also had a chance to ask questions.[11] This process took under ten minutes. Students then completed the endline survey. Out of 528 10th graders who took the PSAT (92.6% of the sophomore class), 440 students took at least one of the surveys and 337 students took both. This sample size is comparable or greater to those in similar studies, such as Zafar (2011) and Stinebrickner and Stinebrickner (2012).

Summary statistics in Table 2 show that students who took the PSAT were more likely to be female, Asian, and white, but not significantly so. Survey participants were, somewhat positively selected from the population of PSAT test-takers.[12] 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

[11] The most common question students asked was whether they had "passed" the PSAT, suggesting they were looking for a simpler way than the percentiles provided in the report to interpret their performance.

[12] There were 3 students who took both surveys but did not take the PSAT. They are excluded from Column 3.

on average 6.5 points higher (about 0.2 standard deviations relative to other Oakland students). As a result, they were also more likely to receive the AP Potential signal. Nevertheless, more than two-thirds of students surveyed were either under-represented minorities or low-income, as defined by eligibility for free or reduced-price lunch.

Table 3 shows summary statistics of student responses in the baseline and endline surveys. To help interpret the means shown, minimum and maximum values and corresponding labels are also provided. The final column shows the mean difference between the endline and baseline surveys and whether it is statistically significant. Of note is the first row, which shows how students adjust their beliefs about their relative PSAT performance. The next set of rows show how self-assessed ability (overall academic ability as well as math, reading, and writing ability) change between the two surveys. All four measures of perceived own ability are adjusted down. In turn, students become more confident in their self-assessments, particularly in their self-assessed PSAT performance, following receipt of their PSAT report. The last rows show expected outcomes. On average, students said they planned to take 1.35 AP courses the following year and adjust this number slightly downward in the endline survey. Students also decrease the likelihood that they will graduate from high school and increase the likelihood that they will attend a community college. As the next section will show, students revise their beliefs differently depending on whether they received a positive or negative information shock.

5 Survey Analysis

5.1 PSAT Scores, AP Potential, and Information Shocks

The survey data collected allows me to back out the information content of the PSAT and AP Potential signal without making assumptions about prior beliefs or the information sets available to the individuals between time t and $t+1$. The only assumption I make in the analysis that follows is that individuals use all available information in forming expectations, and therefore, revisions of expectations are determined solely by new information. As a result, the change in an individual's expectation between time t and time $t+1$ is a function of shocks between time t and $t+1$. In the baseline survey, the student is asked to state his expectation of his perceived relative performance on the PSAT given the information available to him at time t, $E(PSAT_{i,t+1}|\Omega_{i,t})$. I also ask the student to state his revised expectation given the new information available at time $t+1$ following receipt of the PSAT report and informational handout. The change in expectation can be expressed as follows:

Table 3: Summary Statistics of Baseline and Endline Surveys

	Min	Max	Baseline	Endline	Δ
My PSAT score	0	4	2.145	1.962	-0.147***
	Lowest 10%	Highest 10%	(0.743)	(0.938)	
My academic ability	0	4	2.560	2.373	-0.196***
	Lowest 10%	Highest 10%	(0.730)	(0.825)	
My math ability	0	4	2.313	2.207	-0.104***
	Lowest 10%	Highest 10%	(0.904)	(0.947)	
My reading ability	0	4	2.549	2.314	-0.236***
	Lowest 10%	Highest 10%	(0.795)	(0.928)	
My writing ability	0	4	2.354	2.209	-0.153***
	Lowest 10%	Highest 10%	(0.783)	(0.915)	
Confidence in PSAT self-assessment	0	4	2.254	2.682	0.502***
	Not Sure At All	Practically Certain	(0.930)	(0.985)	
Confidence in academic self-assessment	0	4	2.467	2.666	0.244***
	Not Sure At All	Practically Certain	(0.881)	(0.911)	
Confidence in math self-assessment	0	4	2.482	2.678	0.226***
	Not Sure At All	Practically Certain	(0.935)	(0.936)	
Confidence in reading self-assessment	0	4	2.548	2.695	0.213***
	Not Sure At All	Practically Certain	(0.863)	(0.924)	
Confidence in writing self-assessment	0	4	2.486	2.637	0.204***
	Not Sure At All	Practically Certain	(0.862)	(0.935)	
Number of AP classes I plan to take	0	7	1.351	1.240	-0.069*
			(1.141)	(1.102)	
Likelihood I'll pass grad exam 1st time	0	3	2.616	2.595	0.000
	Not At All Likely	Very Likely	(0.560)	(0.632)	
Likelihood I'll take the SAT	0	3	2.652	2.708	0.039
	Not At All Likely	Very Likely	(0.565)	(0.541)	
Likelihood I'll graduate HS	0	3	2.832	2.788	-0.043**
	Not At All Likely	Very Likely	(0.407)	(0.464)	
Likelihood I'll attend community college	0	3	1.367	1.461	0.068**
	Not At All Likely	Very Likely	(0.899)	(0.966)	
Likelihood I'll attend four-year college	0	3	2.480	2.429	-0.024
	Not At All Likely	Very Likely	(0.670)	(0.722	
N			396	381	

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

$$I_{i,t+1} = E(PSAT_i|\Omega_{i,t+1}) - E(PSAT_i|\Omega_i, t), \tag{6}$$

Given that the 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 2 in Section 3. I define the information shock as in equation 6 instead because students are asked about their relative performance and do not have full information about everyone else's scores. In the presence of full information, the two options should be identical. However, this is not the case. Even after receiving their results students still provide their "best guess" of their relative performance. Figure 3 illustrates the distribution of the information shock across the sample. While approximately half of students do not experience any information shock (a value of 0), the remaining do. Among students who experience an information shock, more experience the PSAT as a negative shock than a positive one. The information shock metric varies from -2 (an extreme negative surprise) to 2 (an extreme positive surprise).

Table 4 presents the mean values of both I, the information shock, and what I term "initial overconfidence," the difference between students' initial beliefs and their actual performance, $E(PSAT_i|\Omega_{i,t})-PSAT_{i,t+1}$. Column 3 shows the values of I by ethnicity and gender. The PSAT is a negative information shock on average, but an especially negative shock for black students, followed by Latino and Asian students. For white students, the PSAT constitutes a positive information shock. A comparison of the information shock by gender shows that males experience a stronger negative information shock than females. Column (5) presents the measure of initial overconfidence. Black students are the most overconfident about their performance relative to the rest of the school, as are males. Asian and white students, on the other hand, are initially underconfident in their beliefs about their performance. While students may have somewhat different reference groups due to tracking within the school, black and Latino students participate in similar tracks, as do males and females. These findings are consistent with other studies that have found that men tend to be more overconfident about their ability than women (Niederle and Vesterlund, 2007 and Stinebrickner and Stinebrickner, 2012) and that Asian students report lower self-efficacy beliefs (Martin and Dembo, 1997).

While the high frequency of the baseline and endline surveys allows for the shock to be solely attributable to the PSAT, it is sensible to verify that students revised their beliefs consistently with the information they received. In addition, it is possible that students with different characteristics updated their beliefs in different ways. Table 5 shows the results of regressions of the information shock on students' AP Potential status, PSAT score, and then adds dummies for gender and ethnicity:[13]

$$I_{i,t+1} = \beta_0 + \beta_1 APPotential_i + \beta_2 PSATScore_i + \beta_3 Female_i + \sum_j \beta_j Ethnicity_{ij} + \mu_i$$

The results show that higher PSAT scores and the AP Potential signal resulted in more positive information shocks. Further, students with the same PSAT score who receive the AP Potential signal experience a larger information shock, which suggests that the AP Potential signal contains

[13] The excluded ethnic group is white students.

Figure 3: Distribution of Information Shock

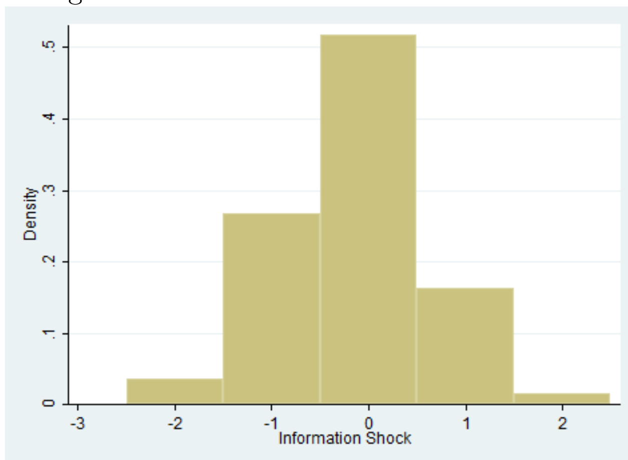


Table 4: Information Shock and Overconfidence

	(1) $E(PSAT_i \mid \Omega_{i,t})$	(2) $E(PSAT_i \mid \Omega_{i,t+1})$	(3) Information Shock	(4) $PSAT_{i,t+1}$	(5) Initial Overconfidence	N
All Students	2.146	2.028	-0.147***	2.221	-0.076	326
	(0.744)	(0.949)	(0.786)	(1.136)	(1.048)	
Male	2.338	2.104	-0.235***	2.255	0.124*	145
	(0.784)	(0.991)	(0.808)	(1.147)	(1.066)	
Female	2.044	1.967	-0.077*	2.293	-0.242***	181
	(0.706)	(0.912)	(0.764)	(1.114)	(1.005)	
Black	2.05	1.674	-0.424***	1.63	0.421***	92
	(0.649)	(0.813)	(0.815)	(0.947)	(1.004)	
Asian	2.208	2.099	-0.127*	2.506	-0.299**	71
	(0.767)	(0.848)	(0.716)	(1.047)	(0.875)	
Latino	1.798	1.5	-0.273***	1.714	0.083	66
	(0.636)	(0.846)	(0.755)	(1.093)	(1.143)	
White	2.489	2.694	0.212***	3.13	-0.641***	85
	(0.749)	(0.802)	(0.742)	(0.745)	(0.859)	

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

information *in addition* to that provided by the PSAT score. The fact that the AP Potential signal contains informational value motivates the next section, which estimates the causal effect of the signal on student's decision-making. Finally, note that although there are differences in the average information shocks experienced by different genders and ethnic groups, once PSAT results and AP Potential status are controlled for, there are no significant differences, with the exception of black students, who experience more negative shocks than white students. In results not shown, I ask

Table 5: Factors Affecting Information Shock

DV: Information Shock	(1)	(2)
AP Potential	0.337**	0.353**
	(0.143)	(0.146)
PSAT Score	0.009***	0.010***
	(0.003)	(0.003)
Female		0.080
		(0.080)
Black		-0.228*
		(0.133)
Latino		-0.097
		(0.143)
Asian		-0.193
		(0.122)
R^2	0.194	0.224
N	326	324

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

whether some students respond to the AP Potential signal more than others by interacting the AP Potential dummy variable by gender and ethnicity. I find no significant differences except for Asian students, who respond to the AP Potential signal less than whites.

5.2 Revisions of Self-Assessed Ability and Expected Outcomes

This section begins by studying how the information shock provided by the PSAT and AP Potential signals led students to revise their beliefs about their own ability. As outlined in the framework in Section 3, individuals' expected ability is a significant input into human capital investment decisions. Students were asked in the survey to place themselves in one of five categories, ranging from highest 10% to lowest 10%, relative to the rest of the school for their overall academic ability A and more specifically, their ability in the areas tested by the PSAT: mathematics M, reading R, and writing W. Table 6 presents the results of the following regression, which examines the relationship between the information shock and students' revised self-assessed abilities.

$$\begin{aligned}\Delta_{Ability_i} &= E(Ability_i|\Omega_{i,t+1}) - E(Ability_i|\Omega_{i,t}) \\ &= \alpha_0 + \alpha_1 I_{i,t+1} + \alpha_2 PSATScore_i + \alpha_3 Female_i + \sum\nolimits_j \alpha_j Ethnicity_{ij} + \upsilon_i\end{aligned}$$

Columns 1, 4, 7, and 10 report estimates from this model, which contains no interaction terms. Students consistently revise their beliefs about own ability in response to the information shock. The higher (the more positive) the value of the shock, the more they increase their beliefs about their ability across all measures. The model controls for the student's PSAT score, which also tends to positively affect the revision of beliefs, and for gender and ethnicity, which are not statistically significant factors. To answer whether students revise their beliefs differently by ethnicity in response to the information shock, I repeat the same model and interact the information shock with a dummy for the student's ethnicity. None of the interaction terms are significant across the four measures of ability and signs and magnitudes are inconsistent, suggesting students of different ethnic groups respond similarly to the information shock. Next I examine differences by gender, interacting the information shock with a female dummy variable. While the estimated coefficient on this interaction is consistently negative, the only instance in which I find a statistically significant difference is in the revision of mathematical ability. In contrast to males, female students hardly adjust their self-assessed ability in mathematics in response to the shock. This result is consistent with past research in psychology that suggests women's perceptions of math ability are more fixed than men's (Dweck, 2007).

Although the results in Table 6 show that self-assessed ability is responsive to the information shock, it is possible that students respond differently to positive versus negative shocks. Table 7 shows the results of a regression that divides the information shock into three types: positive, negative, and zero. Dummy variables for positive and negative shocks are included, and the zero shock dummy is omitted to facilitate interpretation of the coefficients. The results show that the effect of negative shocks on revised self-assessed ability tend to be larger and statistically more significant than the positive shocks. For example, while students who received a positive shock increased their beliefs about their academic ability by 0.187 points on a five-point scale, students who received a negative shock revised their beliefs down by 0.286 points. I repeat the same regression adding interaction terms between the information shock and ethnic groups and gender as before (results not shown), and again find no differential response. Note that because more students received a negative shock than a positive one and a negative shock tends to asymmetrically affect students' perception of their own ability, it is possible that in this context, providing information may do more harm than good. While a rational framework suggests that information leads individuals to make more optimal decisions, it does not take into account psychic costs of experiencing negative information shocks or social optimality.

Table 6: Revision of Self-Assessments

	Δ_A			Δ_M			Δ_R			Δ_W		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Information Shock	0.211***	0.124	0.219***	0.199***	0.274***	0.290***	0.307***	0.260**	0.327***	0.205***	0.213**	0.217**
	(0.054)	(0.102)	(0.068)	(0.052)	(0.090)	(0.072)	(0.076)	(0.126)	(0.098)	(0.067)	(0.092)	(0.089)
PSAT Score	0.003*	0.003*	0.002	0.003*	0.003**	0.002	0.006***	0.006***	0.004***	0.008***	0.008***	0.006***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Black	0.091	0.094		0.006	0.003		0.178	0.231*		0.143	0.117	
	(0.123)	(0.126)		(0.120)	(0.120)		(0.130)	(0.137)		(0.116)	(0.120)	
Latino	0.098	0.069		0.215*	0.217*		0.026	0.033		0.288**	0.366***	
	(0.124)	(0.129)		(0.128)	(0.130)		(0.127)	(0.134)		(0.121)	(0.118)	
Asian	0.096	0.077		-0.061	-0.029		-0.211	-0.240*		-0.145	-0.163	
	(0.094)	(0.099)		(0.112)	(0.111)		(0.134)	(0.140)		(0.112)	(0.113)	
Female	0.049		0.027	-0.061		-0.090	-0.078		-0.073	-0.035		-0.025
	(0.071)		(0.065)	(0.078)		(0.076)	(0.088)		(0.090)	(0.075)		(0.076)
Black X Shock		0.154			-0.141			0.175			-0.079	
		(0.144)			(0.120)			(0.168)			(0.124)	
Latino X Shock		0.074			-0.158			0.083			0.261	
		(0.149)			(0.156)			(0.162)			(0.176)	
Asian X Shock		0.115			0.007			-0.168			-0.184	
		(0.160)			(0.135)			(0.223)			(0.164)	
Female X Shock			-0.025			-0.156*			-0.042			-0.006
			(0.099)			(0.094)			(0.124)			(0.113)
R^2	0.109	0.112	0.096	0.097	0.101	0.088	0.186	0.197	0.160	0.197	0.220	0.155
N	312	312	324	312	312	324	312	312	324	313	313	325

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

Table 7: Revision of Self-Assessments, Positive vs. Negative Shocks

	(1) Δ_A	(2) Δ_M	(3) Δ_R	(4) Δ_W
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)
Black	0.095	0.011	0.181	0.144
	(0.121)	(0.119)	(0.128)	(0.115)
Latino	0.106	0.223*	0.038	0.296**
	(0.123)	(0.127)	(0.126)	(0.121)
Asian	0.093	-0.063	-0.216	-0.149
	(0.092)	(0.111)	(0.134)	(0.112)
Female	0.048	-0.064	-0.077	-0.035
	(0.070)	(0.078)	(0.088)	(0.076)
R^2	0.110	0.103	0.183	0.195
N	312	312	312	313

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

Manski (2004) writes that there is a "critical need for basic research on expectations formation." The present study provides a unique setting to learn how information shocks about own ability affect students' expectations about future, unrealized academic outcomes. In addition to asking students to state their beliefs about their ability, the survey asked about their expectations about the likelihood of the following binary outcomes, not realizable until time $t + n$, where $n > 1$: the likelihood of passing the graduation exit exam in the first attempt, the likelihood of taking the SAT, the likelihood of graduating from high school, and the likelihood of attending community college or a four-year college. In addition, I asked students to state the expected number of AP classes they would enroll in the following year. Although students' beliefs about their ability were consistently revised, I find that the information shock did not lead students to revise their expectations about these future outcomes in the same way. The top panel of Table 8 shows how these expectations are revised after the receipt of information using the following regression model:

$$\begin{aligned}\Delta_{Outcome_{i,t+n}} &= E(Outcome_{i,t+n}|\Omega_{i,t+1}) - E(Outcome_{i,t+n}|\Omega_{i,t}) \\ &= \alpha_0 + \alpha_1 I_{i,t+1} + \alpha_2 PSATScore_i + \alpha_3 Female_i + \sum\nolimits_j \alpha_j Ethnicity_{ij} + \upsilon_i\end{aligned}$$

Although the signs on the information shock coefficient are consistent with the model outlined in Section 3 (that is, students upwardly revise the expectation of positive academic outcomes if they receive positive information, and vice versa), the information shock only appears to cause a statistically significant change in the number of AP courses students believe they will take and the likelihood that they will attend a four-year college.[14] Panel B of Table 8 presents the results of the same regressions using the positive and negative shock dummies defined earlier instead of the single information shock measure. The signs of the estimates on the positive and negative shocks continue to be consistent with the predictions from the model. Focusing just on statistically significant results, Panel B shows that the revisions of expectations about AP course-taking and four-year college enrollment were driven by students who received a *positive* information shock. I include in each regression demographic controls to account for differences in how different groups revise their answers; however, all information shock coefficients are robust to the inclusion or exclusion of these demographic controls. In addition, I again interact the information shock with ethnicity and gender dummy variables (results not shown) but find no statistically significant differences in how different groups use the information shock to revise expectations about future outcomes.

Comparing these results to those on beliefs about academic ability shows that information shocks may affect expectations differently depending on how valuable the information received is to the outcome being predicted. The next section explores this concept more formally, but it is worth noting here that the outcomes most affected tended to be those most emphasized during the presentation of PSAT reports. Students were told about the AP Potential message, were given a list of AP courses offered at the high school, and were provided a PSAT/SAT conversion table to estimate their future SAT performance and a table with the range of SAT scores required for admission into California's public four-year colleges. It seems intuitive, then, that plans for AP enrollment and expectations about attending four-year colleges were more responsive to the information shock received. Though it may seem surprising that students with a large positive shock on the PSAT did not increase their likelihood of taking the SAT, students had already stated a very high likelihood of taking the SAT

[14]While not statistically significant, it is also interesting to note the one negative coefficient in Panel A: a positive information shock led some students to decrease their expected likelihood of attending a community college. The summary statistics in Section 4 show that most students do not think their likelihood of going to a community college is very high, especially compared to the other outcomes. This is inconsistent with past data in which 49% of college-going graduates from Oakland Tech attended a two-year college.

Table 8: Revision of Expected Outcomes

	(1) Δ_{AP}	(2) $\Delta_{GradTest}$	(3) $\Delta_{TakeSAT}$	(4) Δ_{GradHS}	(5) $\Delta_{CommColl}$	(6) $\Delta_{4YrColl}$
			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%.

before receiving the scores (90% of students with a positive shock said they were "very likely" to take the SAT in the baseline survey). In the case of students who revised their belief about passing the graduation test after receiving a negative shock, it is interesting to note that students took the graduation exam, which is an eighth grade level assessment, a week before taking the PSAT in October and had not yet received their results.

5.3 Are revisions consistent with Bayesian updating?

In order to informally test whether students' revised expectations in a manner consistent with Bayesian learning, I asked students how certain they were regarding their beliefs about their relative performance on the PSAT and relative academic ability. I provided categorical options about their level of confidence, ranging from "not sure at all" to "practically certain." As Table 3 in Section 4 shows, students increased their level of confidence regarding each of their beliefs about performance and ability following receipt of information, although there was still a level of uncertainty since students did not have full information about the performance of their peers. Individuals who are

Table 9: Absolute Change in Beliefs as a Function of Certainty in Prior Beliefs

	(1)	(2)	(3)	(4)	(5)
	$\|I\|$	$\|\Delta_A\|$	$\|\Delta_M\|$	$\|\Delta_R\|$	$\|\Delta_W\|$
Initial certainty	-0.051	-0.022	-0.021	-0.007	-0.099**
	(0.036)	(0.038)	(0.035)	(0.052)	(0.043)
PSAT Score	-0.002	-0.003*	-0.001	-0.005***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
R^2	0.035	0.067	0.006	0.063	0.063
N	298	294	295	295	295

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

more confident in their self-assessment are expected to update less in response to new information.

I perform an informal test of Bayesian updating by regressing the absolute value of the change in perceived performance and ability on the student's stated certainty about that response in the initial survey, together with their PSAT score and demographic characteristics. This regression is captured in the following model, and the results appear in Table 9. The coefficients on the "initial certainty" variables are consistently negative, suggesting that individuals who were more confident in the initial survey made smaller absolute revisions in their beliefs. However, only the coefficient on confidence in the initial belief about writing ability is statistically significant. The results are not affected by controlling for demographic characteristics or PSAT scores.

$$|\Delta_{X_i}| = \gamma_0 + \gamma_1 Certainty_{i,t,X} + \gamma_2 PSATScore_i + \zeta_i$$

A more formal way of checking for Bayesian learning is to approximate equation 4 in Section 3, repeated here:

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

where as before, γ represents the relative precision of each signal. Here $\gamma^s = \frac{\rho^s}{\rho^s+\rho^{PSAT}} \in [0,1]$ is the weight assigned to the individual's 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 received from the PSAT. According to equation 4, the posterior belief will be a function of the prior and the new information acquired between period t and $t+1$. In the context of this study, the prior belief refers to the subjective belief elicited in the baseline survey, while the posterior refers to the belief elicited in the endline survey. The coefficients γ^x show the nature of the updating process. One would expect γ^s to be equal to one and γ^I to be equal to zero if the student depends solely on her prior information and does not learn any new information from the PSAT that is relevant to her academic self-assessments and future outcomes. On the other hand, if the new information is very valuable, γ^s would be close to zero and γ^I would be large. Equation 4 is estimated for both self-assessments and expected outcomes using the following regression model:

$$E(Outcome_{i,t+n}|\Omega_{i,t+1}) = \gamma^s E(Outcome_{i,t+n}|\Omega_{i,t}) + \gamma^I I_{i,t+1} + \eta_i$$

The estimates in Table 10 fall between the two extremes, although as expected, the prior belief plays a very significant role in all cases. However, $\hat{\gamma^s}$ is smaller than one, suggesting that the posterior beliefs do not solely depend on the prior belief. The results shows that $\hat{\gamma^I}$ is small in magnitude but statistically significant in students' self-assessment of their academic, math, reading, and writing ability, the expected number of AP classes they plan to take, and the likelihood of attending a four-year college, in line with the previous results regarding revisions of beliefs and expectations. These results are broadly consistent with Bayesian learning and with findings in other studies, such as Zafar (2011).

Of interest is the value of new information relative to the prior, which can be denoted as $V = \frac{\rho^{PSAT}}{\rho^s} = 1/\gamma^s - 1$, the ratio of the precision of the new information, which in this context may be thought of as the perceived relevance of the information, to the precision of the prior. While the PSAT may be a very precise measure of academic ability, if students do not perceive it to be a relevant in the various contexts they are asked to consider, they will not use it to update their beliefs. As earlier results showed, students revise their beliefs about their ability but do not revise their expectations of all future outcomes. Higher values of V would imply greater relative value of the new information for the belief or outcome in question. Table 10 presents the estimates of V below the regression estimates. In most cases, V is very small in magnitude, suggesting that the new information provided by the PSAT and AP Potential signal is not very valuable for most beliefs and academic outcomes relative to the students' priors. However, the notable exception is once again the number of AP classes students expect to enroll in.

6 Identification of the Causal Impact of the AP Potential Signal

The previous section provides strong evidence that the PSAT and AP Potential signal contain valuable information for the decision to enroll in AP classes. However, even if students revise beliefs about their ability and number of AP courses they plan to enroll in, it is possible that they are just temporarily uplifted or de-motivated by their PSAT results, leaving outcomes unchanged. On the

Table 10: Bayesian Updating in Response to New Information

	(1) A_{t+1}	(2) M_{t+1}	(3) R_{t+1}	(4) W_{t+1}	(5) AP_{t+1}	(6) $GradTest_{t+1}$	(7) $TakeSAT_{t+1}$	(8) $GradHS_{t+1}$	(9) $CommColl_{t+1}$	(10) $4YrColl_{t+1}$
Prior Belief	0.925***	0.938***	0.910***	0.933***	0.848***	0.986***	0.991***	0.981***	0.953***	0.976***
	(0.012)	(0.014)	(0.015)	(0.016)	(0.050)	(0.008)	(0.008)	(0.005)	(0.025)	(0.009)
Information	0.242***	0.230***	0.370***	0.306***	0.178***	0.058*	-0.019	0.033	-0.036	0.099**
Shock	(0.049)	(0.046)	(0.060)	(0.057)	(0.049)	(0.035)	(0.041)	(0.022)	(0.064)	(0.042)
R^2	0.944	0.926	0.914	0.918	0.813	0.963	0.961	0.986	0.820	0.958
N	324	324	324	325	270	315	323	318	315	324
V	0.081	0.067	0.099	0.072	**0.179**	0.014	0.010	0.019	0.050	0.025

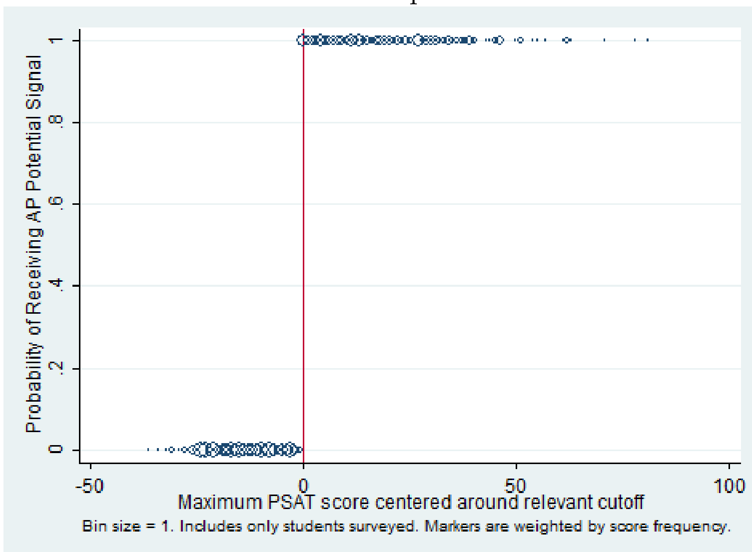
*significant at 10%; ** significant at 5%; *** significant at 1%.

other hand, if the effects on expectations translate into actions, providing a meaningful information signal to students about their ability could be a cost-effective intervention. This section focuses on rigorously identifying the causal effect of the AP Potential signal on AP course enrollment the following year. This outcome is investigated for a few reasons. First, it is precisely the decision that the signal tries to influence. Second, the evidence from the previous section shows that expectations about AP course enrollment were the most affected by the new information received. Finally, course enrollment is the first major outcome observed for students given the timing of the AP Potential signal.

A natural place to start is to ask whether students actually did what they said they would do. Although survey expectations and actual enrollment the following year are strongly correlated, with a correlation coefficient of 0.546, students were overoptimistic in their stated plans. On average, students said they would take 1.2 AP classes, but the mean number of enrolled AP courses was 0.41. Although 87% of students who said they would take zero AP classes actually went on to enroll in none, only half of students who said they would take AP classes actually enrolled in at least one course. Students who upwardly revised their expectations in response to the information shock did enroll in more AP classes compared to those who didn't. These comparisons show that survey responses are indeed meaningful, yet cannot be assumed to fully reflect true beliefs or future outcomes. They also highlight the importance of linking outcomes to expectations in understanding decision-making.

A primary obstacle to identification of interventions like AP Potential is the non-random assignment of treatments. Fortunately, the deterministic nature of the assignment of the AP Potential signal allows the use of a sharp Regression Discontinuity (RD) design to estimate its effect. In the sharp RD design, the treatment $Treat_i$ is a deterministic function of one of the covariates, the assignment variable r: $Treat_i = 1R_i \geq c$. All units with a covariate value of at least c are assigned the treatment, and all units with a covariate value less than c are not assigned any treatment. As explained earlier, AP Potential is first calculated for each AP course using one of seven PSAT scores. Students can meet the criteria for AP Potential in as many as 27 AP courses, each of which uses a different score and cut-point (see Table A.1 in the Appendix). However, succeeding in meeting just one of the 27 conditions would result in the student receiving the AP Potential message on his or her score report. Therefore, we can think of the maximum value of the set of seven scores as the "binding" test for that student. I construct a new variable with each student's binding score, thereby reducing the dimensionality of the problem from seven test scores to one binding score. I also center the binding score around the appropriate cut-point value that applies. Figure 4 confirms that the relationship between the binding score and the probability of receiving the signal is

Figure 4: Deterministic Relationship Between AP Potential and R



completely deterministic using data from all 10th grade students in Oakland in 2013.

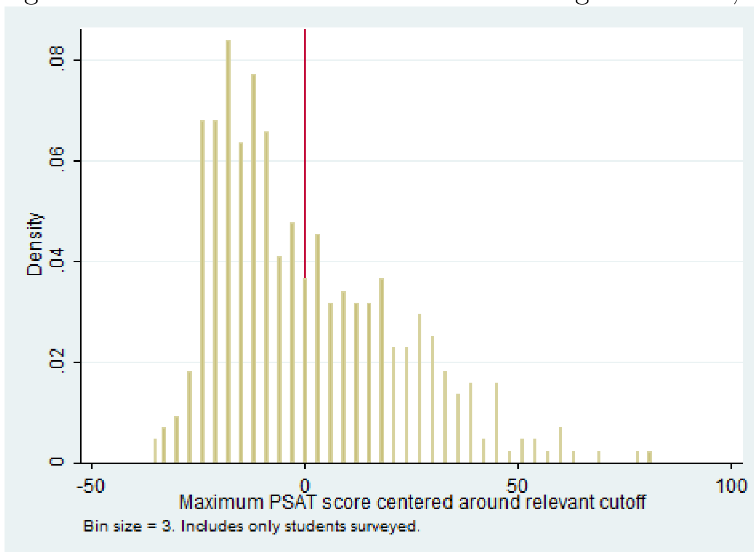
The sharp RD design exploits the discontinuity in the conditional expectation of the outcome given the covariate to uncover an average causal effect of the treatment:

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

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 2007). By design, there are no individuals with $R_i = c$ for whom we observe $Y_i(0)$. Thus, the fact that we observe units with covariate values arbitrarily close to c is exploited, provided that a smoothness assumption about the distribution of the covariate holds. Figure 5 presents the distribution of the binding score variable for a bin size of 3, which is small enough to show how the data behaves, but not so small that it introduces unnecessary noise. As can be seen, there are no discontinuities in the distribution of the this score around the cut-point.[15]

[15] A bin sizes of 3 was selected as an optimal bin size for analysis using both visual inspection and more formal methods. Table A.2 in the Appendix shows the results of an F-test that compares the explanatory power of the assignment variable on the outcome for bin sizes h and $h/2$. This test is based on the idea that if a bin width is too wide, using narrower bins would provide a better fit to the data. A second F-test was also performed which compared the explanatory power of the assignment variable on the outcome for bin sizes h and bin sizes h interacted with the assignment variable. This test suggests that a bin width is too wide if there is still a systematic relationship between the outcome and rating within each bin. If such a relationship exists, then the average value of the outcome within the bin is not representative of the outcome value at the boundaries of the bin (Jacob et al., 2012). The second test yielded the same results as the first. For the complete sample of 2013 students, the optimal bin size appears to be 3,

Figure 5: Distribution of Re-Centered Binding Test Score, R



Because treatment is perfectly correlated with observable characteristics (the PSAT scores), the continuity of unobserved characteristics is sufficient to allow identification of the average treatment effect for marginal students. Nevertheless, it is worth discussing the standard concerns in RD designs. First, the assignment variable cannot be caused by or influenced by the treatment. Because the AP Potential depends fully on PSAT scores, the assignment variable in this case is necessarily measured prior to the treatment. Furthermore, intentional manipulation is implausible. Although students can purposely miss many or all of the PSAT questions, they are not aware of the AP Potential program, making it impossible for them to change the binding score near the cut-point. A second concern is that the cut-point must be determined independently of the rating variable (that is, it must be exogenous). As detailed in Section 3, researchers at the College Board determined the cut-point based on multiple steps of statistical analysis using the national population of PSAT test-takers. In addition, there must be no other relevant ways in which individuals on one side of the cut-point are treated differently from those on the other side, other than the treatment. When students are handed back their PSAT results, the score reports are folded in half, showing only the student's name. The score reports of students I surveyed were locked in the school principal's office until I picked them up prior to distributing them to students. Further, teachers were not aware of the AP Potential signal since 2013 was the first year it appeared on reports. Figure A.5 in the

whereas for the subgroup of the sample of surveyed students, the tests did not restrict the bin size, although visual inspection also supports a bin size of 3. I employ the same bin sizes for all graphical displays, even those not graphing the outcome variable, in order to facilitate comparisons.

Appendix graphs various non-outcome variables, including free or reduced-price lunch eligibility, math and English scores in the California Standards Test (CST) from the previous year, and high school GPA from the previous year against R as a check of the orthogonality of unobservables. No discontinuities are visible, which is consistent with the deterministic nature of the assignment rule.

Thus, comparing the outcome of individuals within a very small interval around the cut-point should be very similar to a randomized experiment at the cut-point (a tie-breaking experiment). That is, because they have essentially the same value of the assignment variable, individuals just below the cut-point score should on average be very similar to individuals just above the cut-point and thus have similar average outcomes in the absence of the treatment as well as similar average outcomes when receiving treatment. Note that this is especially likely in the present case, in which the assignment variable is a score on a standardized assessment, which necessarily will contain some measurement error. With those to the right of the cut-point receiving treatment and those to the left not, a comparison of the average outcomes of both groups should provide a good estimate of the treatment effect. Of course, in the case of varying treatment effects, the estimate will only apply to the subset of individuals close to the cut-point.

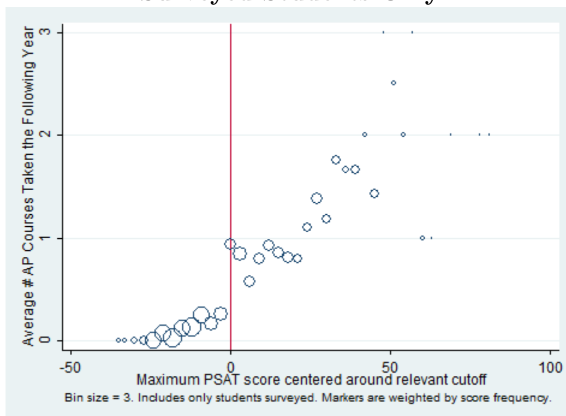
Figure 6 graphs the number of AP courses students enrolled in the academic year after receiving the AP Potential signal. The top graph shows the relationship between this outcome and the assignment variable R (the binding PSAT score centered around the relevant cut-point) just for the students who participated in the survey using a bin size of 3. A distinct jump is visible between the bin just to the left of the cut-point and the cut-point itself, which offers strong evidence that receiving the AP Potential signal led to students on the margin to enroll in more AP classes, consistent with the findings on the value of the information shock and the revision in expectations from the previous section. Since no survey data is required for this analysis, I can expand the sample to include all students who took the PSAT in 2013. The bottom graph depicts the same visualization for this larger sample of students across the district. Interestingly, despite the discontinuity observed for the sample of surveyed students, no distinct jumps are discernable in the bottom graph, regardless of the bin size used.

Table 11 presents the mean values for the bins surrounding the cut-point for both surveyed students and the entire population of 2013 test-takers. The cell mean at the cut-point is about four times larger than the cell mean just left of the cut-point (a difference of 0.675 using a bin size of 3) for surveyed students.[16] When comparing the entire student population, the difference in means

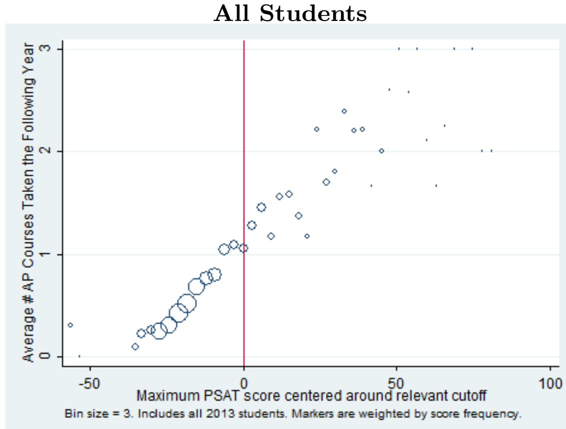
[16]Comparing students within one point of the cut-point to those exactly at the cut-point yields a difference of 1.286. However, because the cell sizes become very small with a bin size of 1, this difference in means could be capturing random error in the data.

Figure 6: Discontinuity in Number of AP Classes Taken a Year Later, Bin Size of 3

Surveyed Students Only



All Students



between these two cells is -0.039 using a bin size of 3). Note that the means in Table 11 are higher for all students than for surveyed students with similar values of R, likely because the students surveyed at Oakland Tech are higher performing than students at other high schools in Oakland, and thus those who participate in AP at the school are more positively selected than elsewhere in the district. In what follows, I use parametric and non-parametric methods to confirm the patterns shown in this section.

6.1 Parametric Estimation

Increasing the interval around the cut-point that is used to compare the outcome of interest is likely to produce a bias in the estimated effect if the assignment variable is related to the outcome variable conditional on treatment status, which tends to be the case. Among students with AP Potential, those with higher PSAT scores are more likely to enroll in AP courses. However, if an assumption is

Table 11: Average Number of AP Courses Taken Around Cut-point

Surveyed Students Only			All Students		
Bin*	AP Courses Taken	N	Bin*	AP Courses Taken	N
-9	.241	29	-9	0.796	113
-6	0.167	18	-6	1.043	93
-3	0.263	19	-3	1.093	75
0	0.938	16	0	1.054	56
3	0.842	19	3	1.280	50
6	0.571	14	6	1.451	51
9	0.800	15	9	1.175	40

*Bins are identified by the left-most value of R.

made about the functional form of the relationship between the average outcome and the assignment variable, it is possible to use more observations and extrapolate from above and below the cut-point (van der Klauww, 2008). This is known as a parametric approach, and is contrasted with the non-parametric strategy explored in the next section, which uses observations from a narrowly defined bandwidth around the cut-point. The tradeoff between these two strategies is one between bias and precision. Since the parametric approach uses all available data in the estimation of treatment effects, it can potentially offer greater precision than the nonparametric, local approach. However, it may be difficult to ensure that the functional form of the relationship between the conditional mean of the outcome and the assignment variable is correctly specified over the entire range of data, and thus the potential for bias is increased. Although non-parametric estimation substantially reduces the chances of bias by using a much smaller portion of the data, in may have more limited statistical power due to the smaller sample size it uses. This is a concern given the small sample size of surveyed students, which the graphical analysis suggests were differentially impacted by the AP Potential signal.

The challenge to parametric estimation is identifying the correct functional form of the relationship between the assignment variable and the outcome in the absence of treatment. A variety of functional forms can be tested to determine which fits the data best, so that bias is minimized. I define six variations of the following model $Y_i = \alpha + \beta_0 Treat_i + f(R_i) + \epsilon_i$ based on different functional forms of $f(R)$:

Model 1 (Linear): $Y_i = \alpha + \beta_0 Treat_i + \beta_1 R_i + \epsilon_i$

Model 2 (Linear Interaction): $Y_i = \alpha + \beta_0 Treat_i + \beta_1 R_i + \beta_2 R_i Treat_i + \epsilon_i$

Model 3 (Quadratic): $Y_i = \alpha + \beta_0 Treat_i + \beta_1 R_i + \beta_2 R_i^2 + \epsilon_i$

Model 4 (Quadratic Interaction): $Y_i = \alpha + \beta_0 Treat_i + \beta_1 R_i + \beta_2 R_i Treat_i + \beta_3 R_i^2 + \beta_4 R_i^2 Treat_i + \epsilon_i$

Model 5 (Cubic): $Y_i = \alpha + \beta_0 Treat_i + \beta_1 R_i + \beta_2 R_i^2 + \beta_3 R_i^3 + \epsilon_i$

Model 6 (Cubic Interaction): $Y_i = \alpha + \beta_0 Treat_i + \beta_1 R_i + \beta_2 R_i Treat_i + \beta_3 R_i^2 + \beta_4 R_i^2 Treat_i + \beta_5 R_i^3 + \beta_6 R_i^3 Treat_i + \epsilon_i$

The first, third, and fifth models constrain the slope of the relationship between outcome and the assignment variable to be identical on both sides of the cut-point, while the other three (2, 4, and 6) specify a different polynomial function on either side of the cut-point. Including an interaction between the rating variable and the treatment can account for the fact that the treatment may impact not only the intercept, but also the slope of the regression line. At the same time, increasing the complexity of the model also reduces the power of the analysis so the simplest model that can maximize fit is preferred. Visual inspection of Figure 6 suggests that the slope of the relationship may be different on both sides of the cut-point. I also follow the procedure outlined in Lee and Lemieux (2010), which tests whether or not there is unexplained variability in the relationship between the outcome and assignment variable that the specified model does not capture, to test the fit of all six models against the data. I also implement the Akaike Information Criterion (AIC) test to determine the relative goodness of fit of each model. The AIC test captures the bias-precision trade-off of using a more complex model by measuring increases in both the estimated residual variance as well as in the number of parameters. Table A.3 in the Appendix shows the results of both tests. None of the functional specifications are rejected by the Lee and Lemieux (2010) F-test, which implies that a simple functional form adequately describes the relationship between the outcome and assignment variable. The AIC values support using a simpler specification, so my preferred model is Model 2 (linear interaction). However, for completeness and as a check for sensitivity, I will present results for all the models.

Panel A of Table 12 shows the treatment effect estimates for the six models with and without covariates (gender, ethnicity, free/reduced-priced lunch eligibility, special education and English learner status, and previous year GPA) for both surveyed students and the overall population. Including additional covariates may eliminate some bias that is the result of using observations far from the cut-point and can improve precision. On the other hand, any violations of the assumption that the covariates included are exogenous and have a linear impact on mean outcomes could increase bias. For surveyed students, the estimates are robust to the inclusion of covariates and only change slightly. Furthermore, the estimates are fairly consistent across the six models, always yielding a positive, statistically significant effect on AP course enrollment even with higher order polynomials that allow for nonlinearity. The parametric results of Model 2 suggest that receiving the AP Potential

Table 12: Parametric Estimates of Impact of AP Potential on AP Course Enrollment

	Panel A: Parametric Estimates on All Values of R			
	Surveyed Students Only		All 2013 Students	
	Without Covariates	With Covariates	Without Covariates	With Covariates
	(1)	(2)	(3)	(4)
Model 1	0.329**	0.347***	0.120	0.080
	(0.128)	(0.122)	(0.099)	(0.092)
Model 2	**0.397*** **	**0.421*** **	0.111	0.098
	(0.114)	**(0.112)**	(0.098)	(0.091)
Model 3	0.400***	0.430***	0.104	0.113
	(0.123)	(0.120)	(0.309)	(0.294)
Model 4	0.340**	0.370**	-0.198	-0.090
	(0.166)	(0.163)	(0.133)	(0.124)
Model 5	0.338**	0.371***	-0.101	-0.040
	(0.144)	(0.138)	(0.118)	(0.110)
Model 6	0.588***	0.619***	-0.083	-0.095
	(0.225)	(0.216)	(0.181)	(0.168)
N	426	422	2009	1935
	Panel B: Parametric Estimates Dropping Outermost 10% of Observations			
Model 1	0.429***	0.422***	-0.102	0.077
	(0.156)	(0.156)	(0.114)	(0.107)
Model 2	**0.433*** **	**0.445*** **	-0.028	0.049
	(0.144)	**(0.142)**	(0.135)	(0.125)
Model 3	0.446***	0.476***	-0.022	-0.002
	(0.144)	(0.143)	(0.151)	(0.140)
Model 4	0.619***	0.657***	-0.123	-0.081
	(0.223)	(0.217)	(0.202)	(0.187)
Model 5	0.602***	0.673***	-0.091	-0.067
	(0.219)	(0.211)	(0.162)	(0.151)
Model 6	0.797**	0.787**	-0.170	-0.192
	(0.317)	(0.309)	(0.281)	(0.259)
N	357	333	1642	1578

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

signal in a context in which it was explained caused surveyed students to enroll in more AP courses, increasing the mean number of courses taken for students on the margin by roughly 0.4 (the mean value on the left-hand size using a bin size of 3 is 0.263). Columns 3 and 4 show the results for the population of PSAT test-takers in Oakland. All the estimates are small in magnitude, statistically indistinguishable from zero, and do not maintain the same sign across specifications. These results are consistent with the graphical evidence in Figure 6: the AP Potential signal did not have an impact on student unless additional information and context was provided. In the case of the students surveyed, who received additional information, the AP Potential signal led to an increase in AP enrollment.

The main concern with global estimators is that they are more sensitive to observations far away from the cut-point, which can have a substantial influence on the estimation of the relationship between the outcome and the assignment variable. To assess how sensitive the functional forms (particularly Model 2, the preferred model) are to the exclusion of these data points, I re-estimate the same models dropping the outermost 10% of data points with the highest and lowest values of R. If the true conditional relationship between the binding score and AP course enrollment has some nonlinearity that has not been captured, the impact estimates will be sensitive to these exclusions. Panel B of Table 12 presents these results of this robustness check. The estimates of the effect on surveyed students are slightly larger on this subset of data, and the standard errors increase due to the smaller sample size. Estimates are statistically significant across specifications and remain insensitive to the inclusion of covariates. The point estimates from Model 2 on surveyed students increases from 0.397 to 0.433. The standard deviation of the outcome is 0.728 for these students, meaning a difference of 0.036 is quite small. The analysis that includes all students again yields no statistically significant results, regardless of the specification used.

6.2 Non-Parametric Estimation: Local Linear Regression

If the functional form used in the parametric regressions is incorrectly specified, treatment effects will be estimated with bias. Non-parametric 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 more likely to be linear (or another order polynomial, in the case of local quadratic regressions and other higher order fits). 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:

$$Y_i = \alpha + \beta_0 Treat_i + \beta_1 R_i + \beta_2 R_i Treat_i + \epsilon_i$$

Thus, the considerations with the local linear regression approach are the choice of bandwidth and the choice of kernel weight. Just as the tradeoff between the global parametric approach and the local linear regression approach is one between precision and bias, the selection of a bandwidth presents the same tradeoff, which is of particular concern given the small sample size of the surveyed group. For the choice of bandwidth, I begin by implementing the Imbens and Kalyanaraman (2009) "plug-in" procedure, which yields an optimal bandwidth of 4. Intuitively, the formula, $h = 1.84 S_R N^{-1/5}$, where S_R is the sample variance of the assignment variable, provides a closed form solution for the bandwidth that minimizes a function of bias and precision.[17]

Although the parametric estimates shown in the previous section do not seem sensitive to removing observations far away from the cut-points, using kernels with compact support such as the uniform, triangle, and Epanechnikov kernels, rules out any sensitivity to such observations, which is an attractive feature given the nature of RD designs (Jacob et al., 2012). I begin by employing a triangle kernel, which decreases the weight placed on observations as the distance to the cut-point increases, unlike the uniform kernel effectively employed in the previous section. In any case, if using different weights impacts the estimates, it likely suggests that the results are highly sensitive to the choice of bandwidth. For this reason, I present results for different bandwidths and different kernels in the Appendix. Results are robust to variations.

Table 13 presents the estimated treatment effects from the local linear regression using a variety of bandwidths. I present results separately for surveyed students only and the population of 2013 test-takers. The result of the local linear regression on surveyed students using the bandwidth of 4 yields a point estimate of the impact of the AP Potential signal on AP course enrollment of 1.050, which is statistically significant at the 1% level. This is a large estimated impact, as the mean number of AP courses students enroll in just left of the cutoff is approximately 0.3 for this sample of students. As the non-parametric model is re-estimated using larger bandwidths, we see (reading down column 1) that the point estimate decreases, staying in the 0.829 to 1.050 range, and the standard error falls as more data are incorporated. Smaller bandwidths yield larger point estimates, as high as 1.581 for a bandwidth of 2 (though, naturally, with a much wider 95% confidence interval of [0.370,2.122]). Estimates on all 2013 students (of which almost a quarter are the surveyed students) are much smaller and generally not statistically significant, except for larger bandwidths. The results of these non-parametric estimates offer strong support for the graphical and parametric evidence presented earlier, and actually estimate a larger treatment effect of receiving the AP Potential signal than

[17] A different approach to selecting the bandwidth is the Cross-Validiation Procedure suggested by Imbens and Lemieux (2008). However, Imbens and Kalyanaraman (2009) show that although the two procedures can yield different bandwidths, they do not result in different estimates. I report results for several bandwidth choices for completeness and as a check of robustness.

Table 13: Non-Parametric Estimates of Impact of AP Potential on AP Course Enrollment

Bandwidth	Surveyed Students Only	All 2013 Students
2	1.581***	0.208
	(0.510)	(0.219)
3	1.246***	0.160
	(0.447)	(0.173)
4	**1.050****	0.182
	(0.437)	(0.150)
5	0.914***	0.228*
	(0.414)	(0.136)
6	0.846**	0.184*
	(0.390)	(0.110)
7	0.813**	0.178*
	(0.360)	(0.103)
8	0.832**	0.169*
	(0.333)	(0.098)
9	0.829***	0.159*
	(0.312)	(0.093)

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

these other approaches.

Figure A.6 in the Appendix graphs the relationship between the bandwidth size and the non-parametric RD estimates on surveyed students using both a triangle kernel (top panel) and rectangular kernel (bottom panel). The estimates are not very sensitive to the choice of kernel, though do tend to be slightly smaller in magnitude with the rectangular kernel. For instance, a bandwidth of 3 yields a point estimate of 1.246 using the triangle kernel and a point estimate of 0.993 using a rectangular kernel, with both estimates statistically significant at the 5% level. Comparing estimates and their confidence intervals across larger bandwidths shows decreasing point estimates and standard errors. Because smaller bandwidths tend to produce lower bias, it is encouraging that point estimates at smaller bandwidths are larger. Given the small sample size, however, there is a loss in precision in employing the non-parametric methods, particularly at the smallest bandwidths. Nevertheless, the estimated impact of receiving the AP Potential signal is statistically greater than zero across estimation methods, specifications, bandwidth sizes, and kernel weights for students who were surveyed.

7 Discussion and Conclusion

By the time they graduate, more than half of white and Asian students in Oakland participate in AP, compared to 27% of Latino students and 18% of black students. These gaps are widened further in the rates of enrollment in selective colleges. Initiatives to reduce ethnic gaps have received a great deal of attention and investment amid claims that high-achieving minority and low-income students are being overlooked. As Hoxby and Avery (2012) and Dillon and Smith (2012) show, however, this is largely due to high-performing students from disadvantaged backgrounds opting not to apply. In Oakland, this pattern begins before graduation with the decision to participate in AP, a key step on the path to admission into selective four-year colleges. Among students who meet the AP Potential criteria, 35% of black students and 27% of Latino students never enroll in AP, compared to fewer than 10% of comparable white and Asian students.

The results from this paper suggest that providing customized information about ability to qualified candidates who may not otherwise consider enrolling in AP or applying to selective colleges could be a cost-effective, high-leverage intervention. The types of students affected by the AP Potential signal are precisely those targeted by policymakers. Although their scores barely meet the signal's cut-point, they are still relatively high-performing, scoring above the 75th percentile among Oakland students. In addition, two-thirds of the surveyed students just above the cut-point belong to under-represented minority groups or low-income families (over half were under-represented minorities). Despite small sample sizes (and thus wider confidence intervals), RD estimates not shown performed separately for students from disadvantaged groups support the notion that these students responded to the information signal similarly to their more advantaged counterparts.

The effects of receiving information about ability identified in this paper also shed light on the question of academic mismatch. Dillon and Smith (2012) find substantial amounts of both undermatch (high ability students at unselective colleges) and overmatch (low ability students at selective colleges). All else equal, having access to additional information about ability should reduce matching error in enrollment decisions. However, one concern with the AP Potential signal is that because it summarizes the results of 27 subject-specific conditions, it could actually induce mismatch, particularly for students at the margin. For example, a student who barely meets the AP Spanish Literature threshold based on his PSAT reading and writing scores may not be a good candidate for AP Calculus. On the other hand, if students use all of the information contained in the PSAT reports (which primarily consist of students' performance on the three sections of the test), the danger of mismatch may be lower.[18]

[18]Subject-specific AP Potential information is available on the My College QuickStart website. However, as noted

The most common subjects to trigger the AP Potential signal are Spanish Literature (61.2%), Calculus BC (24.9%), and Psychology (13.5%). However, neither Spanish Literature nor Psychology were offered at Oakland Tech in 2014 (or at most Oakland schools, for that matter). The fact that some of these courses are not offered further raises the concern for mismatch. Most of the surveyed students at the margin of AP Potential enroll 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 are three times more likely to enroll in AP Calculus than students whose binding subject was Spanish Literature, suggesting that students also employ other sources of information about their ability in selecting courses.

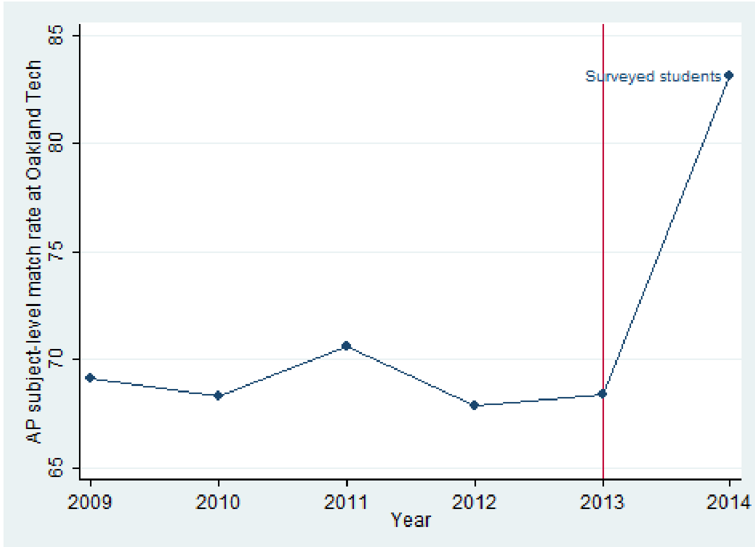
To further understand subject-specific mismatch, I define a match indicator for each student-subject pairing that equals 1 if the student's AP course enrollment matches her AP Potential in that subject. The match rate between AP course enrollment and subject-specific AP Potential is 55% across the district. However, a significant portion of the mismatch is due to limited course offerings relative to the number of AP subjects in which students can have AP Potential. Juniors have access to about a dozen AP courses at large schools like Oakland Tech. For offered courses, the match rate increases to about 73%. Surveyed students had an AP course enrollment match rate of 83%, suggesting that access to information in fact reduces matching error. Comparing match rates at Oakland Tech over the last six years in Figure 7, I find a sizeable increase following the information intervention provided in 2013.

Among students surveyed, 3.5% of student-course enrollment pairings were overmatched and 13.5% were undermatched. Some level of undermatch is to be expected because high-ability students cannot take all the AP classes offered in a given year. Of possible concern is the fact that overmatched enrollments, though smaller in number, are much more likely to come from minority students. However, it is unclear whether undermatch and overmatch should be treated equally. Dillon and Smith (2012) find suggestive evidence that students with information about their ability 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, it appears this opinion is also shared by policymakers. There is some evidence in support of this belief. Examining overmatching due to affirmative action, Bowen and Bok (1998) find no impact on degree completion for overmatched students.

The subject-specific match rates mask the fact that many more students who do not meet any AP Potential criteria enroll in AP compared to those who meet the criteria but do not enroll. Figure A.7 in the Appendix groups PSAT test-takers depending on whether they met any of the

earlier, usage rates are low among Oakland students.

Figure 7: AP Subject-Level Match Rates at Oakland Technical High School



AP Potential criteria and whether they enrolled in any AP course. Given the high proportion of students in AP who do not meet the AP Potential criteria (an especially large share among black and Latino students), overmatching may be a larger concern than undermatching in low-performing schools. However, if the benefits of overmatching 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. Further research on the effects of overmatching in both high school and college is needed.

One result of overmatching in AP can be low AP exam pass rates. Lichten (2010) notes that as more students enroll in AP, there are high failure rates in AP exams. Oakland has high failure rates in AP exams, despite the fact that students tend to do well in the courses (see Figure A.8 in the Appendix, which illustrates the distribution of course grades versus exam pass rates). Students pass about 90% of AP classes, but only 38% of AP exams. However, passing rates are much higher, at 75%, for students with AP Potential and are similarly high for students just above the cut-point, suggesting that students at the margin are well prepared to earn AP college credit. Whether there are other causal effects from participating in AP is a major gap in the education literature that has been pointed out by economists like Klopfenstein and Thomas (2009).

There is also a need for research on the effects of negative information shocks on human capital investments, especially given the large share of students overmatching. The survey analysis showed that students responded differently to negative shocks compared to positive shocks. In particular, these students' absolute revisions of self-assessed academic ability were much larger than those of students who experienced a positive shock. Because AP Potential is framed as a positive signal, future work should study the effects of negative information signals of ability. One such example is California's Early Assessment Program, which informs students in their junior year of high school whether they will need remediation in college. The test was designed with the intention of decreasing the high rate (approximately 60%) of first-time freshmen admitted to California State Universities requiring remediation.

This paper also contributes to the literature that seeks to understand how information shocks affect expectations formation and decision making.[19] I establish that the PSAT, the first national college aptitude test offered in high school, and the AP Potential signal both contain valuable information that leads individuals to revise beliefs about ability and future academic plans in a manner consistent with Bayesian learning. Intuitively, the informational value of this particular information shock was greatest for revisions of expected AP course enrollment. Following students into the next academic year, I find that the effect on expectations is borne out in enrollment decisions. Students on the margin of receiving the AP Potential signal enroll in approximately one more AP course their junior year, effectively increasing participation in the AP program. As additional time elapses, I plan on studying outcomes extending beyond course enrollment.

Only the students who received an explanation of their PSAT results, the AP Potential signal, and ways to use the information responded to the signal, however. The AP Potential message is not especially conspicuous on PSAT reports, so students who were surveyed likely received an intensified treatment. Participating in the survey did not provide a differential treatment to students *at the margin* of AP Potential. Although surveyed students were positively selected from the Oakland population, participation in the survey did not jump at the AP Potential cut-point (see Figure A.9 in the Appendix, which plots the probability of participating in the survey against binding scores). Further, when score reports were distributed and discussed, the content of the reports was sealed until opened by the student. Also note that including demographic and academic covariates did not have a notable effect on the RD estimates for either the subsample of surveyed students or the total population.

Thus, the most likely explanation for why a treatment effect was only detected for surveyed students is that the additional information they received intensified the signal's underlying effect. This result has an immediate implication for the College Board and schools. In order for the AP Potential signal to have the intended effect of influencing AP course enrollment, educators and counselors

[19]For examples of related studies outside of education, see Hurd and McGarry (2002), Lochner (2007), and Smith et al. (2001).

should be encouraged to discuss the information provided in the reports as they are distributed to students. Finally, policymakers should consider crafting similar interventions that provide valuable, individualized information about ability tailored to different human capital investment decisions. Information interventions could be a very cost-effective means of influencing high-ability students from under-represented groups to apply to selective colleges or enroll in competitive majors.

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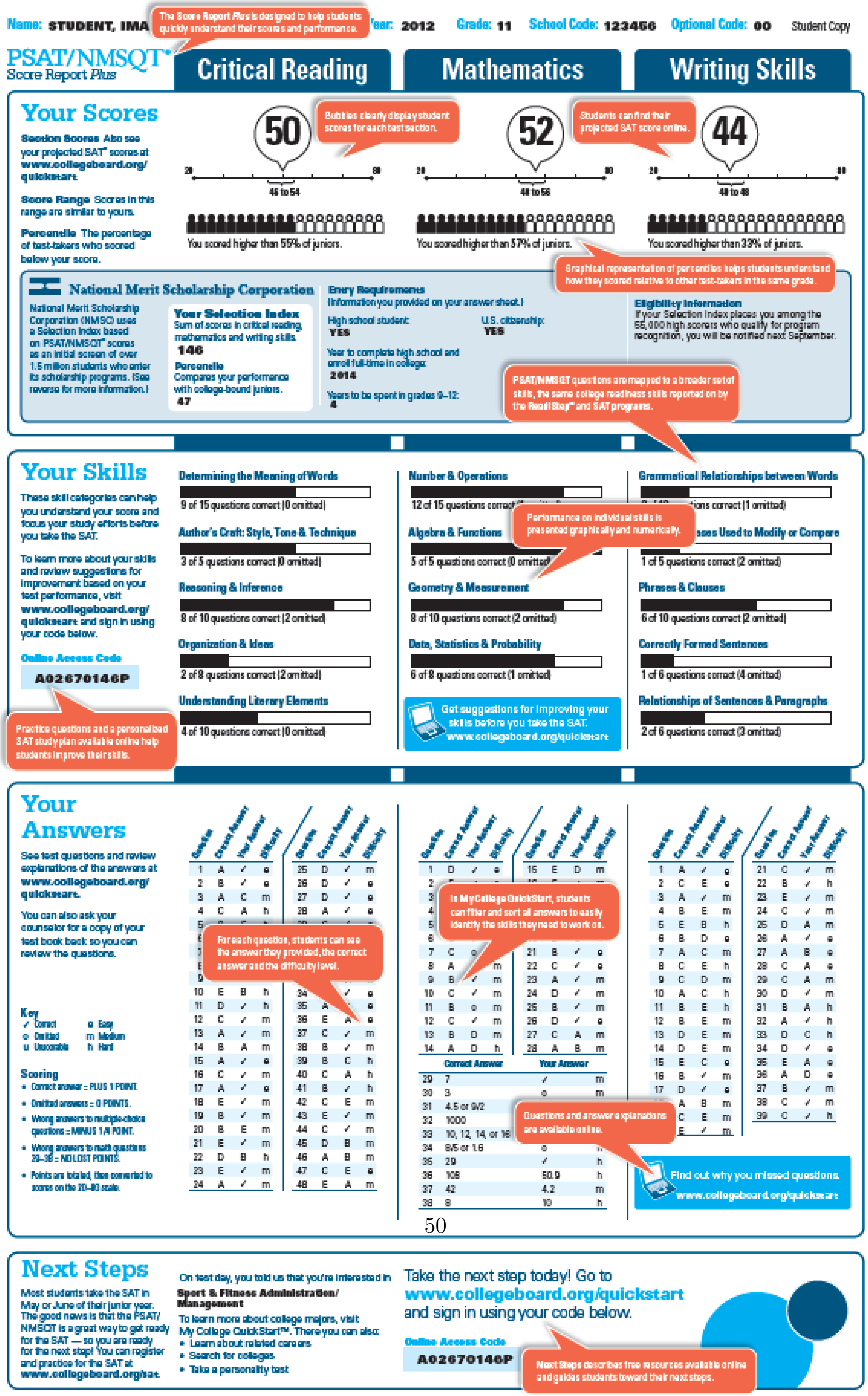
A Appendix

Table A.1: AP Potential Cut-point Rules

AP Subject	Offered in OUSD	AP Potential Rule	Students with AP Potential
Art History		$R + W \geq 106$	0.100
Biology	Y	$M + R \geq 114$	0.082
Calculus AB	Y	$M \geq 60$	0.103
Calculus BC	Y	$M \geq 56$	0.060
Chemistry	Y	$R + M \geq 115$	0.078
Chinese	Y	n/a	
Comparative Gov't & Politics		$R + M + W \geq 166$	0.084
Computer Science	Y	$R + M \geq 114$	0.082
English Language	Y	$R + W \geq 97$	0.153
English Literature	Y	$R + W \geq 106$	0.100
Environmental Science	Y	$R + M \geq 110$	0.101
European History		$R + M + W \geq 151$	0.132
French	Y	n/a	
Human Geography		$R + M + W \geq 153$	0.123
Macroeconomics	Y	$R + M \geq 116$	0.071
Microeconomics		$R + M \geq 111$	0.095
Music Theory		W + $M \geq 108$	0.089
Physics B	Y	$R + M \geq 116$	0.071
Physics C: Electricity & Magnetism		$R + M \geq 122$	0.066
Physics C: Mechanics		$R + M \geq 117$	0.047
Psychology		$R + M + W \geq 145$	0.164
Spanish Language	Y	n/a	
Spanish Literature	Y	$R + W \geq 88$	0.223
Statistics	Y	$R + M \geq 112$	0.090
U.S. Gov't & Politics	Y	$R + M + W \geq 166$	0.084
U.S. History	Y	$R + M + W \geq 157$	0.112
World History	Y	$R + M \geq 104$	0.129

Figure A.1: 2012 PSAT Results Report


Name: STUDENT, IMA Year: 2012 Grade: 11 School Code: 123456 Optional Code: 00 Student Copy

The Score Report Plus is designed to help students quickly understand their scores and performance.

PSAT/NMSQT® Score Report Plus

Critical Reading | Mathematics | Writing Skills

Your Scores

Section Scores Also see your projected SAT® scores at www.collegeboard.org/quickstart.

Score Range Scores in this range are similar to yours.

Percentile The percentage of test-takers who scored below your score.

Critical Reading: 50 (46 to 54). You scored higher than 55% of juniors.

Mathematics: 52 (48 to 56). You scored higher than 57% of juniors.

Writing Skills: 44 (40 to 48). You scored higher than 33% of juniors.

Bubbles clearly display student scores for each test section.

Students can find their projected SAT score online.

Graphical representation of percentiles helps students understand how they scored relative to other test-takers in the same grade.

National Merit Scholarship Corporation

National Merit Scholarship Corporation (NMSC) uses a Selection Index based on PSAT/NMSQT® scores as an initial screen of over 1.5 million students who enter its scholarship programs. (See reverse for more information.)

Your Selection Index Sum of scores in critical reading, mathematics and writing skills. 146

Percentile Compares your performance with college-bound juniors. 47

Entry Requirements (Information you provided on your answer sheet.)

High school student: YES

U.S. citizenship: YES

Year to complete high school and enroll full-time in college: 2014

Years to be spent in grades 9–12: 4

Eligibility Information If your Selection Index places you among the 55,000 high scorers who qualify for program recognition, you will be notified next September.

PSAT/NMSQT questions are mapped to a broader set of skills, the same college readiness skills reported on by the ReadiStep™ and SAT programs.

Your Skills

These skill categories can help you understand your score and focus your study efforts before you take the SAT.

To learn more about your skills and review suggestions for improvement based on your test performance, visit www.collegeboard.org/quickstart and sign in using your code below.

Online Access Code A02670146P

Practice questions and a personalized SAT study plan available online help students improve their skills.

Determining the Meaning of Words: 9 of 15 questions correct (0 omitted)

Author's Craft: Style, Tone & Technique: 3 of 5 questions correct (0 omitted)

Reasoning & Inference: 8 of 10 questions correct (2 omitted)

Organization & Ideas: 2 of 8 questions correct (2 omitted)

Understanding Literary Elements: 4 of 10 questions correct (0 omitted)

Number & Operations: 12 of 15 questions correct

Algebra & Functions: 5 of 5 questions correct (0 omitted)

Geometry & Measurement: 8 of 10 questions correct (2 omitted)

Data, Statistics & Probability: 6 of 8 questions correct (1 omitted)

Performance on individual skills is presented graphically and numerically.

Get suggestions for improving your skills before you take the SAT. www.collegeboard.org/quickstart

Grammatical Relationships between Words: questions correct (1 omitted)

Phrases Used to Modify or Compare: 1 of 5 questions correct (2 omitted)

Phrases & Clauses: 6 of 10 questions correct (2 omitted)

Correctly Formed Sentences: 1 of 6 questions correct (4 omitted)

Relationships of Sentences & Paragraphs: 2 of 6 questions correct (3 omitted)

Your Answers

See test questions and review explanations of the answers at www.collegeboard.org/quickstart.

You can also ask your counselor for a copy of your test book back so you can review the questions.

Key: ✓ Correct, o Omitted, u Unscorable; e Easy, m Medium, h Hard

Scoring
- Correct answer = PLUS 1 POINT.
- Omitted answers = 0 POINTS.
- Wrong answers to multiple-choice questions = MINUS 1/4 POINT.
- Wrong answers to math questions 29–38 = NO LOST POINTS.
- Points are totaled, then converted to scores on the 20–80 scale.

For each question, students can see the answer they provided, the correct answer and the difficulty level.

In My College QuickStart, students can filter and sort all answers to easily identify the skills they need to work on.

Questions and answer explanations are available online.

Find out why you missed questions. www.collegeboard.org/quickstart

Next Steps

Most students take the SAT in May or June of their junior year. The good news is that the PSAT/NMSQT is a great way to get ready for the SAT — so you are ready for the next step! You can register and practice for the SAT at www.collegeboard.org/sat.

On test day, you told us that you're interested in **Sport & Fitness Administration/Management**

To learn more about college majors, visit My College QuickStart™. There you can also:
- Learn about related careers
- Search for colleges
- Take a personality test

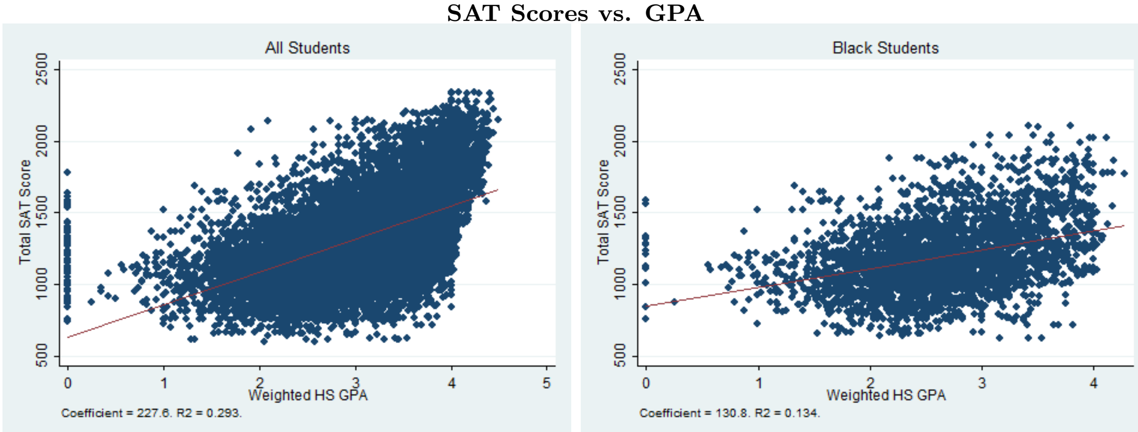
Take the next step today! Go to www.collegeboard.org/quickstart and sign in using your code below.

Online Access Code A02670146P

Next Steps describes free resources available online and guides students toward their next steps.

Figure A.2: SAT Scores, PSAT Scores, and High School GPA

SAT Scores vs. GPA



SAT Scores vs. PSAT Scores

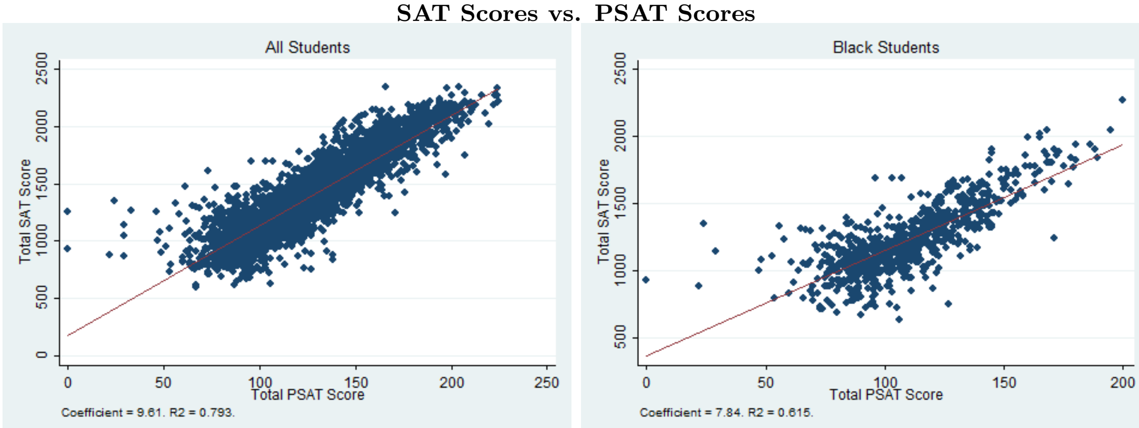


Figure A.3: Survey Instrument

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%
(SAMPLE) I think my height is...				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...					

	Practically Certain	Very Sure	Fairly Sure	Somewhat Sure	Not Sure At All
(SAMPLE) I think my height is...		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.4: 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	650-730
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	420-490	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	730-780	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	730-780	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					

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: Specification Test for Selecting Optimal Bin Width

Bin Size	Number of Bins K	F-Value	Critical Value $F_{K,N-K-1}$
9	17	0.979	1.629
8	18	0.921	1.629
7	22	0.973	1.569
6	24	0.461	1.545
5	28	0.231	1.505
4	33	0.764	1.466
3	43	0.475	1.412
2	63	0.973	1.348
N = 440			

Table A.3: Tests of Model Fit

	Surveyed Students Only		Entire 2013 Sample	
	AIC	F-Value	AIC	F-Value
Model 1	825.90	1.307	26501.61	3.54***
Model 2	825.85	1.217	26503.21	3.52***
Model 3	826.67	1.251	26503.32	3.59
Model 4	829.66	1.226	26441.28	1.39
Model 5	825.30	1.249	26476.89	2.74***
Model 6	825.79	1.481	26442.70	1.36

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

Figure A.5: Relationship Between Non-Outcome Variables and R

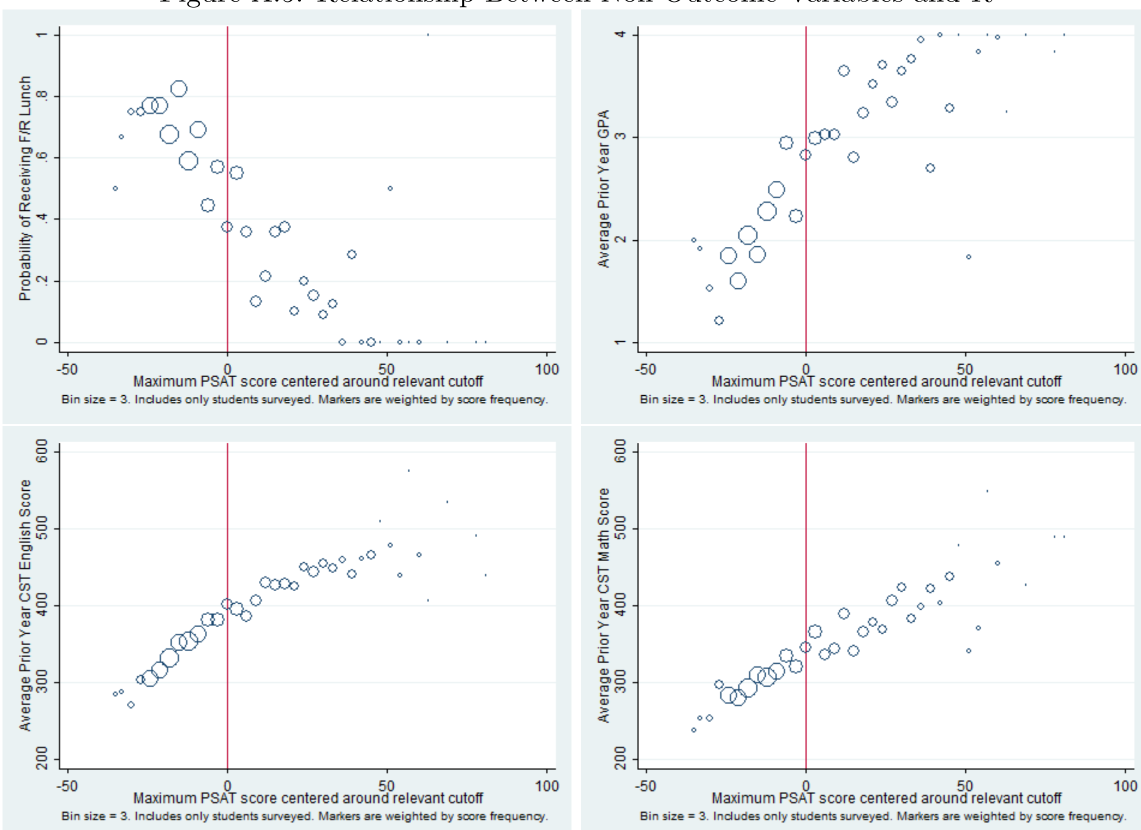
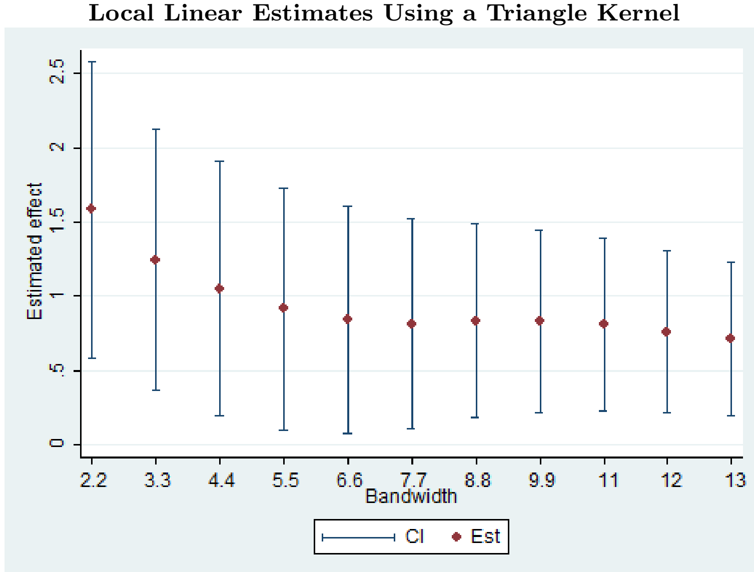


Figure A.6: Relationship Between Bandwidth and Non-Parametric Estimates on Surveyed Students

Local Linear Estimates Using a Triangle Kernel



Local Linear Estimates Using a Rectangle Kernel

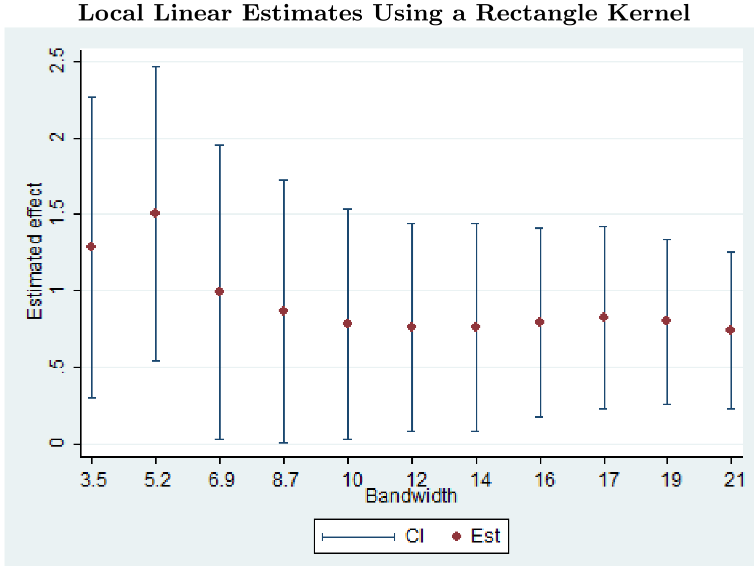


Figure A.7: AP Potential and AP Enrollment

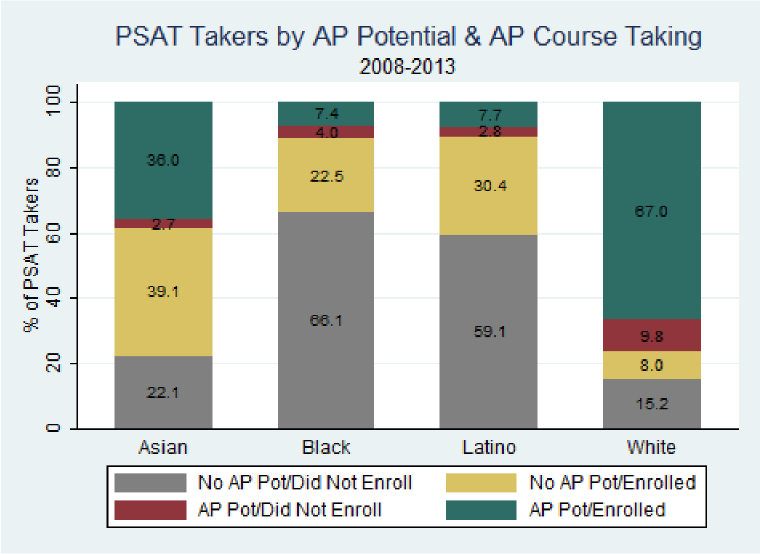


Figure A.8: AP Exam Passing by AP Course Grade

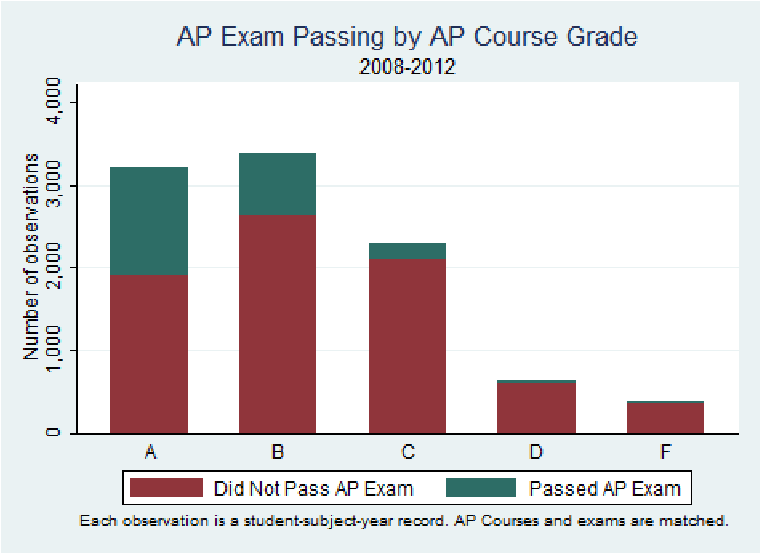


Figure A.9: Relationship between the Probability of Participating in Survey and R