Updating Human Capital Decisions: Evidence from SAT Score Shocks and College Applications

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We estimate whether students update the colleges to which they consider applying in response to large, unanticipated information shocks generated by the release of SAT scores—a primary factor in admission decisions. Exploiting population data on the timing of college selection and a policy that induces students to choose colleges prior to taking the exam, we find that students update their portfolios in terms of selectivity, tuition, and sector. However, the magnitude of updating is too modest to significantly reduce unexplained variation across students, suggesting that nonacademic factors are the dominant determinants of college match.

I. Introduction

A large literature considers the role played by nonacademic determinants of college choice, such as tuition rates and parental resources. Updating de-

We thank Peter Arcidiacono, Marigee Bacolod, Latika Chaudhary, Jesse Cunha, Jessica Howell, Michael Hurwitz, Tyler Ransom, and Hajime Shimao as well as seminar participants at Purdue University, the Graduate School of Business and Public

[*Journal of Labor Economics*, 2018, vol. 36, no. 3]
 0734-306X/2018/3603-0007$10.00
Submitted July 6, 2016; Accepted March 13, 2017; Electronically published April 10, 2018

cisions to reflect new information about academic ability provides an important alternative to such explanations. Thus, recent studies have examined how the revelation of college grades affect students' dropout decisions and choice of major (Zafar 2011; Arcidiacono, Hotz, and Kang 2012; Stange 2012; Stinebrickner and Stinebrickner 2012, 2013; Wiswall and Zafar 2015; Arcidiacono et al. 2016). This study provides a direct analogue at another crucial time for human capital investment: when high school students select colleges to which they may apply. Specifically, we examine whether students update the colleges to which they send their SAT scores in response to large, unanticipated positive and negative information shocks generated by the release of scores. Entrance exam scores are perhaps the most important new information students receive during the college selection process. Thus, if students do not update their portfolios in response to their scores, it indicates that college selection is largely predetermined by nonacademic factors and preexisting beliefs. The estimates provide new causal evidence about how human capital preferences are formed and why college mismatch occurs.[1]

The primary challenge in estimating whether students update is the need to observe their college choices before and after new academic information is revealed. Unfortunately, a student has only one realized application portfolio and, in many cases, receives only one entrance exam score. To overcome this, we exploit a College Board policy that induces students to select a limited number of colleges to receive their SAT scores at the time they register for the exam.[2] Subsequently, students receive their scores and decide whether and where to send additional reports. Using new population data that include the exact date when each college was selected by the student, we are able to estimate the effect of SAT information shocks on the composition of the colleges selected. That is, we exploit a design that contrasts the colleges chosen before the SAT with those chosen after scores are released.

Several factors make this environment a nearly ideal context for identifying the extent to which students update the colleges they select. First, many

Policy at the Naval Postgraduate School, and Maastricht University for helpful comments. The opinions in this paper are those of the authors and may not represent the views of the College Board. Contact the corresponding author, George Bulman, at gbulman@ucsc.edu. Contact Timothy N. Bond, Xiaoxiao Li, and Jonathan Smith at tnbond@purdue.edu, xiaoxiao.s.li@villanova.edu, and jsmith500@gsu.edu, respectively. Information concerning access to the data used in this paper is available as supplementary material online.

[1] The college selection process is important in part because of the potentially high returns to attending a more selective college. For estimates of these returns, see Behrman, Rosenzweig, and Taubman (1996), Black and Smith (2006), Hoekstra (2009), and Cohodes and Goodman (2014).

[2] See Pallais (2015) for an analysis showing that students tend to use the free score reports that are available prior to taking the exam. Three-quarters of SAT takers in our data use at least one of their free reports.

students experience large SAT score shocks that are difficult to anticipate—the standard deviation of within-student differences between first and second SAT scores is 70.3 points, or 0.35 standard deviations. Second, we measure updating using the high-stakes selection of colleges to receive scores rather than using the subjective survey responses that are common in the updating literature. Third, the data used for analysis include students' Preliminary SAT/National Merit Scholarship Qualifying Test (PSAT) scores and, in many cases, two or more SAT attempts. Multiple exams allow us to measure what information is new to the student and to test whether students anticipate their scores. Finally, the analysis is based on national administrative data that produce precise estimates and allow us to consider heterogeneous effects across student ability and socioeconomic characteristics.

There are a number of reasons to believe that students should alter their college choices in response to SAT score shocks. Most notably, entrance exam scores and high school grades are typically the most important factors used by colleges when making admission decisions. This is evident from the widespread and often mechanical use of admission indices that are a function of grade point average (GPA) and exam score by public universities.[3] In addition, students may update their beliefs about their likelihood of being successful at more selective colleges given new objective information about their ability relative to a national pool of college-bound students. Identification of updating is based on a difference-in-differences style design that estimates the extent to which colleges selected before and after students learn their scores reflect this new information. We present an empirical model analogous to those used in the employer-learning literature that reveals several important considerations for the interpretation of the reduced-form results.[4] The model confirms that students should place greater importance on SAT scores as they are released and reduce their reliance on measures of ability that were previously used to anticipate scores. We show that estimates of updating will be biased to the extent that students anticipate

[3] For example, admission indices are used by Alabama State, Iowa State, Utah State, the University of Memphis, the University of Southern Florida, the University of Colorado System, and the California State University System. Similarly, minimum SAT score admission requirements are used by the University of Mississippi, the University of Florida, Kansas State University, and the University System of Georgia. Authors' estimates for eight state universities indicate that the SAT and high school GPA are the dominant determinants of college admission.

[4] The model is closely related to those presented in Farber and Gibbons (1996), Altonji and Pierret (2001), and Lange (2007). The updating that occurs when students' scores are released shares similarities with the updating by employers when they observe the performance of employees (Arcidiacono, Bayer, and Hizmo 2010; Rockoff et al. 2012; Kahn and Lange 2014). Student updating plays a significant role in theoretical models of college choice (Manski 1989; Altonji 1993; Altonji, Blom, and Meghir 2012).

their scores or employ time-varying strategies that are correlated with ability, and we show how to correct for these issues.

The estimates reveal that an unanticipated positive (negative) shock causes a student to select a portfolio that has higher (lower) selectivity, tuition, graduation rates, fraction of private colleges, and geographic dispersion. However, the estimated effects are quite modest: after scoring 100 points higher on the SAT than anticipated, a student will select colleges whose matriculating students scored about 5 points higher on the exam. The magnitude of updating is even smaller when the cumulative portfolio is considered because students select about half the colleges before taking the exam. Thus, a 1 standard deviation SAT score shock results in an approximately 0.10 standard deviation shift in the selectivity of newly added colleges and a 0.05 standard deviation shift in the selectivity of the cumulative portfolio. The magnitude of these effects is one-tenth of the size observed in the cross section, where a 1 standard deviation difference in SAT scores is associated with a 0.4 standard deviation difference in portfolio selectivity after controlling for a rich set of covariates. The disparity between our causal estimates and the cross-sectional correlation implies that much of the apparent match between student ability and college quality is due to unobserved nonacademic factors rather than sorting on academic qualifications. Inertia due to factors such as parental knowledge, financial resources, and geographic preferences results in new information closing a small fraction of the portfolio gap evident across students.

Students who take the SAT two or more times experience multiple information shocks. We find that the composition of colleges selected after the first exam more closely reflects the first score, and likewise for colleges selected after the release of the second score. Importantly, the results indicate that students do not incorporate information from the second score into their choices when only the first score is known, supporting the validity of the empirical design. That many students do not send reports to additional colleges after taking the SAT generates even more inertia in portfolio choice, so we present a lower-bound response in which nonsenders are assumed to not update their portfolios.

Two interesting forms of heterogeneity are evident in the analysis. First, higher-ability students update their portfolios significantly more than lower-ability students. This is consistent with students who conduct national searches more fully incorporating changes in admissions probabilities into their decisions than students who may restrict attention to local universities. Second, students who receive positive shocks update the selectivity of their portfolios significantly more than those who receive negative shocks. These results are supported by evidence that changes in portfolios are driven by students sending their scores more aggressively to selective "reach" colleges with little change in the less selective "safety" colleges.

A number of studies in the literature have found that human capital decisions are sensitive to perceived returns and expectations (Attanasio and Kaufmann 2009; Jensen 2010; Jacob and Linkow 2011; Abramitzky and Lavy 2014), performance labels (Papay, Murnane, and Willett 2016), and parental perceptions of children's ability (Dizon-Ross 2017). Nonetheless, significant mismatch between student ability and college quality has been well documented (Arcidiacono 2005; Arcidiacono, Khan, and Vigdor 2011; Hoxby and Avery 2013; Smith, Pender, and Howell 2013; Arcidiacono and Lovenheim 2016; Dillon and Smith 2017). The modest effect of academic qualifications in this study is consistent with evidence that college choices are shaped by nonacademic factors, such as counseling services (Avery and Kane 2004; Oreopoulos and Ford 2016; Carrell and Sacerdote 2017), information about the cost of college (Bettinger et al. 2012; Hoxby and Turner 2014), and ease of access to entrance exams (Klasik 2013; Bulman 2015; Hurwitz et al. 2015; Goodman 2016). The estimates reveal the role played by entrance exams in shaping college choices, shed light on how students update their human capital decisions, and add causal evidence to our understanding of college mismatch.

The paper is organized as follows. Section II describes the policy and administrative data used to conduct the analysis. Section III introduces an empirical framework of student updating and identifies several testable implications. Section IV presents the primary specifications and results. Section V discusses the implications of the findings.

II. SAT Scores and College Score Reports

This paper uses administrative records from the College Board that include each SAT score and the exact timing of when students send score reports to colleges. Therefore, our data take the form of a panel with colleges selected during multiple information periods: before the exam, after scores are released, and, for two-time takers, after scores for the second exam are released. Panel data provide an opportunity to factor out unobserved, time-invariant individual and household characteristics and beliefs that influence college choices. This section details the content of the individual-level administrative records, the construction of the sample for analysis, and the magnitude and predictability of within-student variation in exam performance.

A. Administrative Data

The SAT is a college entrance exam administered by the College Board that is taken by high school students across the United States, typically in their junior or senior year. The exam consists of math and critical reading sections scored between 200 and 800, so students can receive a combined score between 400 and 1,600.[5] Each section was normalized in 1995 to have a mean score of 500 and a standard deviation of 110. The distribution of

[5] A writing section was introduced in 2005 but is not taken by all students or used by all colleges for admissions.

combined scores is presented in figure 1. Along with scores for each SAT attempt, the data contain scores for the PSAT, which is a lower-stakes version of the SAT taken in a student's sophomore or junior year of high school. PSAT scores range from 40 to 160, so they are multiplied by 10 to have the same scale as SAT scores. The College Board also administers a questionnaire on exam registration that asks students to provide their high school GPA, race, parental income, high school attended, and home zip code.

The analysis in this paper examines the colleges to which students send their SAT scores via the College Board. When registering for the SAT, students have the option to send their scores to four colleges at no additional cost. They must select the colleges within 9 days of taking the exam, so a high fraction of takers elect to send reports before the exam. After this period, scores may be sent for a fee of approximately $11 each. Students from lower-income households are eligible to send additional reports for free. The analysis focuses on years prior to 2009, during which all of a student's scores are reported to a college. In later years, Score Choice policies allowed students to choose which scores are sent, which significantly complicates the empirical design necessary to measure updating. Colleges do not automatically receive a new report if a student retakes the exam. Thus, a student may send a report more than one time to the same college, which is particularly common among those who improve their scores.

Starting in 2007, the data include the exact date that students request each report, making it possible to separate the reports into information periods. For students who took the SAT once, we divide score reports into those requested before taking the exam and those requested after the scores are released.[6] For students who take the SAT twice, we consider reports requested before the first exam, after the first exam score is released but before the second exam is taken (including reports that are free with the second registration), and after the second exam score is released. Each report sent to a 4-year college is merged with college characteristics from the National Center for Education Statistics Integrated Postsecondary Education Data System. We then calculate the average characteristics of the colleges in each period, including the SAT scores of matriculating students, in-state tuition, graduation rate, fraction private, and distance from the student's home. The distribution of portfolio quality in the preexam period is presented in figure 1.

Because there is no national administrative database of college applications, studies have used score reports as a proxy for applications when studying the effects of affirmative action (Long 2004; Card and Krueger 2005), tuition levels (McDuff 2007), guaranteed admission programs (Andrews, Ranchhod,

[6] Score send requests are delayed until new scores are available, so the analysis is based on the request date rather than the fulfillment date. About 3% of students make requests immediately after the exam is taken but before the scores are released. These requests are excluded because they may reflect partial treatment.

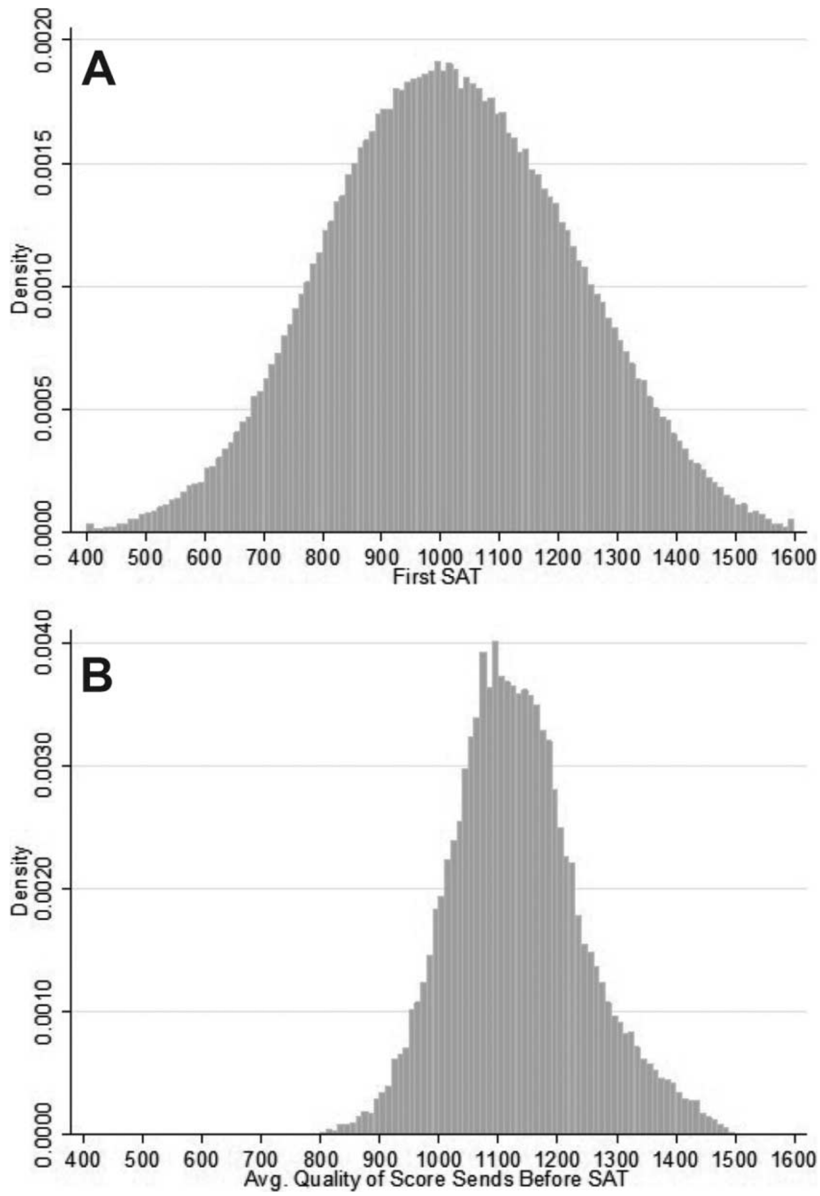

FIG. 1.—Distribution of SAT scores and portfolio quality. *A*, Distribution of first SAT scores. *B*, Distribution of preexam college portfolios. *A* presents the score distribution of students' first SAT scores. The score is measured in multiples of 10 points. The standard deviation of the distribution is 200 points. *B* presents the distribution of the average SAT scores of matriculates of colleges in each student's score report portfolio (one measure of portfolio quality) in the preexam period. The standard deviation of the distribution is 110 points. A color version of this figure is available online.

and Sathy 2010), score report fees (Pallais 2015), and application patterns (Bound, Hershbein, and Long 2009). In many contexts, the fact that students can send score reports to colleges to which they do not apply creates a wedge between the desired outcome (applications) and the observed outcome (score reports). However, score reports are advantageous for examining how students update their beliefs over time. While most applications are completed after students take the SAT, score reports reveal students' choices before and after the exam. Furthermore, completed applications are endogenous to the updating we wish to estimate. For example, a student may send a score report to a selective college prior to taking the SAT and not apply after receiving a lower-than-expected score.

Nonetheless, the evidence suggests that there is a strong (although not one-to-one) relationship between score reports and applications. Because more than 80% of traditional 4-year colleges recommend or require entrance exam scores to be considered for admission, score reports largely define the set of 4-year colleges to which a student could apply. Consistent with this, Card and Krueger (2005) find a "very high" correlation between application and score report totals for universities, and Smith (2016) finds that high-ability, low-income students report applying to more than 60% of the colleges to which they send score reports. Pallais (2015) finds a somewhat weaker relationship when estimating the responsiveness of students to additional free reports.

B. Population for Analysis

The analysis is based on the population of students who took the PSAT and SAT between 2007 and 2009 and who sent at least one score report before taking the SAT. The PSAT is taken by more than 75% of SAT takers and provides students with a measure of how they might perform on the SAT. Approximately 75% of SAT takers send at least one free score report to a college prior to taking the exam, and nearly two-thirds of these students use all four of their free reports. Table 1 presents summary statistics for the population of PSAT takers who took the SAT one or two times and for the subset of these students who sent score reports before and after the exam. Among one-time takers who send reports after the exam, 49% are male, 14% are black, and 13% are Hispanic. Mean PSAT and SAT scores are 1,085 and 1,136, respectively. Two-time takers who send reports are quite similar, with 46% male, 11% black, and 12% Hispanic and average scores of 1,086 on the PSAT and 1,114 on the first SAT. Relative to the population of takers, these students have similar demographic characteristics but higher average performance on the PSAT and SAT.[7]

[7] SAT takers who did not take the PSAT have similar demographic characteristics (51% are male, 11% are black, and 13% are Hispanic) but have lower performance on the SAT, with an average score of 958 points.

Table 1
Summary Statistics

	Sample		Population	
	Mean (1)	SD (2)	Mean (3)	SD (4)
One-time takers:				
Male	.490	.500	.470	.499
White	.608	.488	.588	.492
Black	.136	.343	.161	.368
Hispanic	.133	.340	.158	.365
Other race	.123	.328	.093	.290
PSAT score	1,084.8	218.7	972.0	208.6
SAT score	1,135.5	220.0	1,009.3	213.5
Students	129,039		627,190	
Two-time takers:				
Male	.463	.499	.452	.498
White	.605	.489	.604	.489
Black	.113	.317	.138	.345
Hispanic	.116	.320	.128	.334
Other race	.166	.372	.131	.337
PSAT score	1,085.6	190.9	1,010.8	192.1
First SAT score	1,113.7	185.5	1,038.0	190.6
Second SAT score	1,146.4	190.9	1,064.4	196.6
Students	111,520		534,399	

NOTE.—This table presents summary statistics for the population of students who took the Preliminary SAT/National Merit Scholarship Qualifying Test (PSAT) and the SAT one or two times as well as for those students who sent score reports to colleges before and after receiving their exam scores. All students included in this table took the PSAT as either a sophomore or a junior in high school. The cohorts included in the analysis graduated from high school between 2007 and 2009. The PSAT score has been multiplied by 10 to be on the same scale as the SAT score.

Table 2 presents the correlates of retaking the SAT. Larger score shocks, approximated by the difference between the SAT and PSAT scores, are only weakly correlated with taking the exam twice. For example, having an SAT score that is 100 points lower than one's PSAT is associated with an increase in the retake rate of 2 percentage points. By comparison, students from the highest income category are 9 percentage points more likely to take the exam than those in the lowest income category, and 1 GPA point is associated with an 11 percentage point higher rate of retaking. Thus, higher-income and higher-performing students are overrepresented in the sample of two-time takers. To ensure that splitting the sample does not bias the estimates, we replicate the design for a merged sample of one- and two-time takers.

The analysis is necessarily restricted to students who send score reports before and after taking the SAT. Columns 3 and 4 of table 2 reveal that students from higher-income households and who have higher high school GPAs are more likely to send additional score reports after receiving their scores. In contrast, the estimates do not reveal that students who receive the largest information shocks are more likely to send additional reports. For

Table 2
Retaking the SAT and Sending Score Reports

	Retook SAT		Sent Postexam Reports	
	(1)	(2)	(3)	(4)
$\lvert$SAT − PSAT$\rvert$	−.0004***	.0002***	.0000	−.0002***
	(.0000)	(.0000)	(.0000)	(.0000)
$\lvert$SAT − PSAT$\rvert$ × positive		−.0007***		.0003***
		(.0000)		(.0000)
PSAT score	−.0001***	−.0002***	.0003***	.0003***
	(.0000)	(.0000)	(.0000)	(.0000)
High school GPA	.1058***	.1144***	.0788***	.0764***
	(.0009)	(.0009)	(.0009)	(.0009)
Male	−.0215***	−.0164***	−.0165***	−.0179***
	(.0009)	(.0009)	(.0009)	(.0009)
Asian	.0881***	.0852***	.0341***	.0349***
	(.0019)	(.0019)	(.0020)	(.0020)
Black	−.0031*	−.0114***	.0597***	.0620***
	(.0017)	(.0017)	(.0017)	(.0017)
Hispanic	−.0163***	−.0214***	−.0012	.0003
	(.0017)	(.0017)	(.0017)	(.0017)
Parental income:				
$50,000–$100,000	.0570***	.0585***	.0331***	.0327***
	(.0013)	(.0013)	(.0013)	(.0013)
More than $100,000	.0904***	.0923***	.0499***	.0494***
	(.0015)	(.0015)	(.0015)	(.0015)
Observations	1,157,855	1,157,855	1,157,855	1,157,855
R^2	.066	.070	.073	.073

NOTE.—This table examines the determinants of whether students retake the SAT and whether they send additional score reports. Columns 1 and 2 examine the extent to which student characteristics, household characteristics, and the magnitude of the score shock are correlated with retaking the exam. Columns 3 and 4 examine the extent to which these factors are correlated with sending additional score reports after taking the exam. Each specification includes the number and quality of reports sent before taking the SAT as additional control variables. GPA = grade point average; PSAT = Preliminary SAT/National Merit Scholarship Qualifying Test.
* Significant at the 10% level.
*** Significant at the 1% level.

example, a 100-point shock is associated with a less than 1 percentage point increase in the probability of sending additional reports. Nonetheless, students who send more reports may be those who are more sensitive to new information. Thus, we implement a bounding exercise in Section IV.E in which students who do not send additional reports after receiving their scores are included in the sample under the assumption that they did not update.

C. Within-Student Variation in Scores

There is significant within-student variation in scores earned on college entrance exams. This variation generates the information shocks necessary to identify updating and determines the importance of updating in practice. Figure 2*A* presents the distribution of the differences between students' first SAT scores and their PSAT scores. The mean is close to 0, and the standard

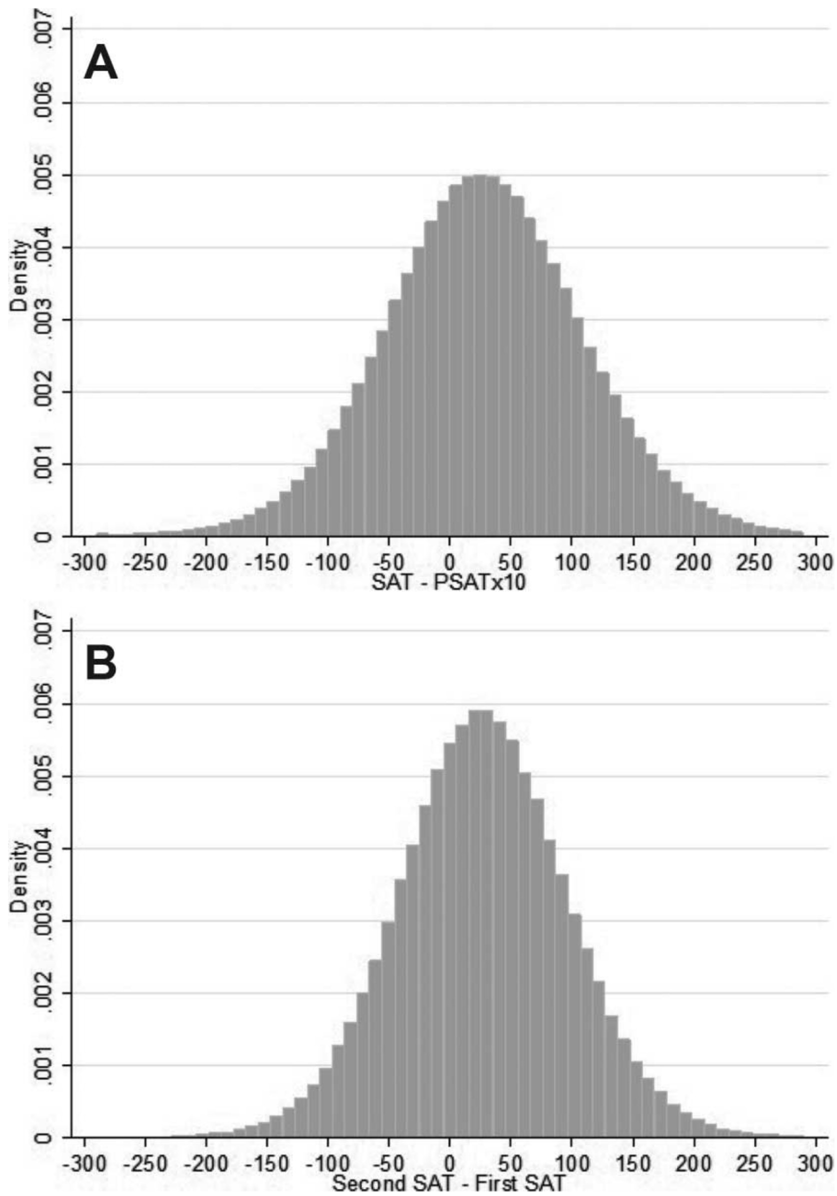

FIG. 2.—Within-student variation in scores: Preliminary SAT/National Merit Scholarship Qualifying Test (PSAT), first SAT, and second SAT. *A*, First SAT − PSAT. *B*, Second SAT − first SAT. *A* presents the difference between a student's SAT and PSAT scores. The PSAT score has been multiplied by 10 to be on the same scale as the SAT score. The standard deviation of the difference is 85.6 points. *B* presents the difference between a student's second SAT score and first SAT score. The standard deviation of the difference is 70.3 points. A color version of this figure is available online.

deviation of the difference is 85.6 points. Thus, within-student variation is nearly one-half of the 190-point standard deviation across students. To examine the extent to which other factors may explain this variation, we generate a predicted SAT score using a rich set of observables in addition to the PSAT, including fixed effects for preexam portfolio selectivity, high school GPA, household income, gender, and race. The standard deviation of the difference between each student's actual and predicted SAT score is 80.5 points.[8] Thus, the PSAT score appears to be the most important predictor of a student's SAT score for the researcher and perhaps for the student as well.

Within-student variation in scores is also evident when students take the SAT multiple times. Figure 2*B* presents the distribution of the differences between students' first and second scores. The standard deviation of the difference is 70.3 points. This variation is especially interesting considering that the exams are, by design, equally difficult and cover the same body of knowledge. Note that while students perform slightly better on average the second time they take the exam, the mean improvement of 30 points is modest relative to the magnitude of the variation. As a result, nearly 40% of students earn a lower score when they take the exam a second time. This is notable because repeat takers have additional time for test preparation and experience taking the exam, and they may have chosen to retake it in part because they had an unexpectedly poor performance the first time. We predict each student's second score using all of the observables listed above in addition to the first SAT score. The resulting standard deviation of the difference is 63.6 points.[9] That is, even with two measures of exam performance in hand, the PSAT and the first SAT, realized performance varies considerably and is difficult to predict. In Section IV, we supplement this descriptive evidence with an empirical test of whether students can anticipate their scores, exploiting the fact that anticipation will reveal itself as the incorporation of future scores into current portfolio choice.

III. Empirical Framework

We develop an empirical model that highlights several important considerations for interpreting the reduced-form estimates. Intuitively, updating should result in positive coefficients on scores as they are released (i.e., students give weight to information as it becomes available) and in negative coefficients on factors such as PSAT scores (i.e., students rely less on other measures of ability). The model also reveals methods for detecting and correcting two sources of bias in the estimates. First, if students partially antic-

[8] While the PSAT has an R^2 of 0.86 for predicting SAT scores, the R^2 for all other covariates (including GPA and demographics) is 0.43.

[9] The addition of GPA and demographic covariates increases the R^2 of the model only from 0.88 to 0.89. Without the PSAT and first SAT, other covariates explain 38% of the variation in the second SAT score.

ipate their scores using factors that are unobserved by the researcher, then the estimates of updating will be attenuated. Intuitively, the magnitude of the information shock for the student is smaller than what is observable in the data. Second, students may employ strategies such as sending scores to "safety" colleges before the exam and "reach" colleges after (or vice versa). If these strategies are correlated with ability, then the estimates will be biased. We present a method to account for time-varying strategies and show that the effect of the second score after only the first score is released can be used to recover causal effects.

A. Student Updating

The empirical model is analogous to those in the employer-learning literature (Farber and Gibbons 1996; Altonji and Pierret 2001; Lange 2007) but with students updating their portfolios in response to receiving new information from the SAT. We present the model for students who take the exam twice, which accounts for one-time takers as a special case. Students form beliefs about optimal portfolios, which can be summarized by a single continuous measure of quality y.[10] The portfolio is a function of three components: s are characteristics observable to the student and the researcher (e.g., PSAT scores), q are characteristics observable only to the student (e.g., personal essays), and z is the true SAT score that a student would receive in the absence of measurement error.[11] We assume that the distribution of (s, q, z) is jointly normal with nonnegative correlations across vectors. This assumption has been made previously in the literature (e.g., Lange 2007) and makes the model tractable, and there are several opportunities in the empirical analysis to examine if it is reasonable.[12] The optimal portfolio for a student i is assumed to be linear in these elements:

[10] We abstract from the method by which a student determines the optimal portfolio and only assume that there is a monotonic relationship between portfolio quality and student characteristics. For theoretical treatments of the portfolio choice problem, see Epple, Romano, and Sieg (2006), Chade, Lewis, and Smith (2014), and Fu (2014).

[11] A fourth factor that can affect the portfolio are time-invariant characteristics unobservable to the student and the researcher (e.g., confidential letters of recommendation), often designated as η in the employer-learning literature. In practice, these factors do not add intuition or alter the results of the model and thus are omitted for brevity. The model differentiates between a true SAT score and the score a student earns, which allows the full set of scores to matter when individuals take the exam multiple times. As our analysis focuses on years prior to Score Choice, colleges observe and may use the full set of scores for admissions decisions. For students who take the exam only once, imposing that the true score is equal to the earned score has no consequences for the results.

[12] If the normality assumption is violated, then the expectations become linear projections and the signs of the predictions still hold.

$$y_i = \delta q_i + rs_i + z_i. \tag{1}$$

Since y_i has no natural scale, we normalize it so that the marginal effect of the true SAT score is equal to 1. Students select colleges to receive reports at $t = 0$ without knowing either SAT score, receive their first score (z_1) at $t = 1$ and choose additional colleges, and receive their second score (z_2) at $t = 2$ and choose colleges with knowledge of both scores. These scores are imperfect signals of z: $z_t = z + \epsilon_t$, where ϵ_t is a normally distributed measurement error term with mean zero and variance σ_ϵ^2 and $E[\epsilon_j \epsilon_k] = 0, \forall j \neq k$.

It follows from joint normality that students' expectations of their scores prior to knowing the results of either exam can be written as $z = E[z|s, q] + \nu = \gamma_1 q + \gamma_2 s + \nu$, where ν is a mean-zero random variable with variance σ_ν^2. In this expression, γ_1 and γ_2 reflect the extent to which students predict their SAT scores using unobservable and observable characteristics, respectively. At no point does a student observe the true score z, only the imperfect signals z_1 and z_2. After each score is announced, students update their beliefs and rely less on q and s to predict their true scores:

$$\begin{aligned} E[z|s, q, z_1] &= (1 - \pi_1)(\gamma_1 q + \gamma_2 s) + \pi_1 z_1, \\ E[z|s, q, z_1, z_2] &= (1 - 2\pi_2)(\gamma_1 q + \gamma_2 s) + \pi_2 z_1 + \pi_2 z_2. \end{aligned} \tag{2}$$

The extent to which students update their beliefs depends on how accurate they believe their priors to be relative to actual exam scores. Specifically, the exams will receive weight $\pi_t = \sigma_\nu^2/(\sigma_\epsilon^2 + t\sigma_\nu^2)$, which follows from Bayesian updating with a normally distributed prior and t normally distributed signals. Note that if students believe revealed scores to be very informative of z or only care about the admissions implications of realized scores, then π_1 is close to 1, and if the test score is relatively uninformative, π_1 is close to 0. Similar intuition applies for π_2. Substituting the expressions from equation (2) into equation (1), we can write the portfolios a student selects in each period as follows:

$$\begin{aligned} y_0 &= [\delta + \gamma_1]q + [r + \gamma_2]s, \\ y_1 &= [\delta + \gamma_1(1 - \pi_1)]q + [r + \gamma_2(1 - \pi_1)]s + \pi_1 z_1, \\ y_2 &= [\delta + \gamma_1(1 - 2\pi_2)]q + [r + \gamma_2(1 - 2\pi_2)]s + \pi_2 z_1 + \pi_2 z_2. \end{aligned} \tag{3}$$

The weight students place on unobservable characteristics q and observable characteristics s prior to learning exam scores is the sum of their direct effects on portfolio choice (δ and r) and their role in predicting unobserved SAT scores (γ_1 and γ_2). Students rely less on these characteristics after the release of the first score z_1 (evident from the $1 - \pi_1$ term) and further reduce this reliance after the release of the second score (evident from the $1 - 2\pi_2$

term). The importance of each realized score is a function of the perceived accuracy of the exam.

B. Coefficient Estimates and Bias

This section presents the composition of the reduced-form coefficients, potential sources of bias, and methods for correcting bias. In practice, we observe s and the two test scores, z_1 and z_2, but not unobservables q. Because (s, q, z) are jointly normal, the conditional expectation of q given s and z and the linear projection are equivalent:

$$q = E[q|s, z] + u = \gamma_3 s + \gamma_4 z + u. \tag{4}$$

In this expression, γ_3 and γ_4 reflect the extent to which students' observable characteristics and true SAT scores are predictive of their unobservable characteristics. As we do not observe z but instead z_1 and z_2, the researcher's expectation is

$$E[q|s, z_1, z_2] = [\gamma_3 + \gamma_4(1 - 2\phi_2)]s + \gamma_4\phi_2 z_1 + \gamma_4\phi_2 z_2, \tag{5}$$

where ϕ_2 is the standard coefficient from Bayesian updating with two independent and identically distributed (i.i.d.) normal signals and reflects that more weight is placed on s due to the noisiness of z_1 and z_2 as predictors of z.

A difference-in-differences design that interacts all observables with an indicator for each time period will reveal how the coefficients on the test scores change as the scores are revealed to the student. We can define the following regressions of y on s, z_1, and z_2 in each period:

$$\begin{aligned} E^*[E[y|s, q]|s, z_1, z_2] &\equiv a_0 s + b_0 z_1 + c_0 z_2, \\ E^*[E[y|s, q, z_1]|s, z_1, z_2] &\equiv a_1 s + b_1 z_1 + c_1 z_2, \\ E^*[E[y|s, q, z_1, z_2]|s, z_1, z_2] &\equiv a_2 s + b_2 z_1 + c_2 z_2. \end{aligned} \tag{6}$$

We can determine the coefficients by substituting equation (5) into equation (3):

$$\begin{aligned} a_0 &= r + \delta[\gamma_3 + \gamma_4(1 - 2\phi_2)] + [\gamma_2 + \gamma_1\gamma_3 + \gamma_1\gamma_4(1 - 2\phi_2)], \\ b_0 &= \gamma_4\phi_2(\delta + \gamma_1), \\ c_0 &= \gamma_4\phi_2(\delta + \gamma_1). \end{aligned} \tag{7}$$

Although the student does not observe z_1 and z_2 prior to taking the exam, the scores will have positive coefficients because they are correlated with the omitted variables q. These coefficients have two components. The first, δ, is time invariant and reflects that q has a causal effect on y. The second is a time-varying "anticipation" effect γ_1, which captures that students use unobservables q to predict z before the test scores arrive. The magnitudes are scaled up or down by the correlation between the unobservables and the true scores z (γ_4) and by the accuracy of realized scores as predictors of z (ϕ_2). Note that if realized scores are i.i.d. draws from the distribution of the true latent score, then $b_0 = c_0$, which provides a natural test of the validity of this assumption (i.e., the first and second SAT scores should have the same coefficients prior to either score being released).

After the first score is revealed, substituting equation (5) into equation (3) reveals that the coefficients change as follows:

$$\begin{aligned} a_1 - a_0 &= -\pi_1[\gamma_2 + \gamma_1\gamma_3 + \gamma_1\gamma_4(1 - 2\phi_2)], \\ b_1 - b_0 &= \pi_1(1 - \gamma_1\gamma_4\phi_2), \\ c_1 - c_0 &= -\pi_1\gamma_1\gamma_4\phi_2. \end{aligned} \tag{8}$$

As expected, students increase their reliance on the revealed scores and reduce their reliance on other measures of ability. However, the difference-in-differences coefficient $b_1 - b_0$ on z_1 is biased downward. It reflects both the causal estimate of updating, π_1, and a decrease in the reliance by the student on q to predict z ($\gamma_1\gamma_4\phi_2$ is the anticipation term). The more accurately students can predict their scores using factors that we cannot observe, the more we will underestimate their response to new information. Fortunately, the magnitude of the bias is captured by the coefficient on the not-yet-revealed second score, z_2. Thus, the difference $(b_1 - b_0) - (c_1 - c_0)$ yields π_1, the causal effect of updating.

Substituting equation (5) into equation (3) also reveals the estimates after both exam scores are released and can be expressed as follows:

$$\begin{aligned} a_2 - a_0 &= -2\pi_2[\gamma_2 + \gamma_1\gamma_3 + \gamma_1\gamma_4(1 - 2\phi_2)], \\ b_2 - b_0 &= \pi_2(1 - 2\gamma_1\gamma_4\phi_2), \\ c_2 - c_0 &= \pi_2(1 - 2\gamma_1\gamma_4\phi_2). \end{aligned} \tag{9}$$

With all scores available to students, they further reduce their reliance on observable characteristics and now place positive weight on the second exam score. As in the preexam period, the coefficients on the first and second SAT scores are equal if realized test scores are i.i.d. There is, however, no longer a natural correction for bias during this period.

We note that it is likely that students employ portfolio selection strategies that vary over time for reasons other than updating. For example, students may send scores to low-risk safety colleges before taking the exam and defer decisions about reach colleges until after learning their scores. These strategies will be innocuous if the changes over time are uncorrelated with the determinants of the optimal portfolio, as level changes are captured by time period fixed effects. However, higher-ability students might have larger or smaller average gaps between their safety and reach colleges than lower-ability students for reasons unrelated to updating. Time-varying strategies can be incorporated into the model by allowing the scale of y to differ across periods. Specifically, we allow students to select portfolios of quality y after the exam and portfolios of quality $\Omega_0 y$ before the exam. A value of Ω_0 that is less than 1 indicates that higher-ability students choose more selective colleges after the exam relative to the preexam period than do lower-ability students (and vice versa for Ω_0 greater than 1). Failure to adjust for this scaling will generate a mechanical bias in the estimates. For instance, if $\Omega_0 < 1$, the coefficient on the SAT in the postexam period will reflect both updating and bias caused by higher-ability students applying more aggressively after the exam for reasons unrelated to score shocks.[13]

To correct for bias caused by time-varying strategies, we estimate the scaling factors explicitly and use them to adjust the portfolio scales in each period. Consider a regression of y_t on observable information about ability s. As originally shown by Farber and Gibbons (1996), this estimate will simply be $E^*[\Omega_t E[y|s]|s] = \Omega_t E^*[y|s]$, where the equality follows from the law of iterated projections. We estimate this using a series of regressions:

$$y_t = d_t s + \epsilon_t. \tag{10}$$

If the coefficient vector on s changes across time periods, it can be attributed only to changes in strategy. The estimate of Ω_t is then $\hat{\Omega}_t = d_t/d_T$, where we normalize to period 1 scale for one-time takers and period 2 scale for two-time takers.

IV. Estimates of Student Updating

College entrance exams are required by the vast majority of 4-year colleges and are a primary factor in admission decisions. Thus, the revelation of scores may be the single largest academic information shock that students experience with respect to shaping college choice. We employ a difference-in-differences style design to estimate whether and to what extent students update the portfolio of colleges to which they send score reports in response to the revelation of their performance. The primary outcome of interest is college selectivity as measured by the average SAT scores of matriculating students. In addition, we examine alternative measures of college quality, including tuition levels, graduation rates, sector, and geographic proximity, and consider heterogeneity by student ability and whether the score shock

[13] For example, for one-time takers the estimate of updating will be $b_1 - \Omega_0 b_0$, which is larger than $b_1 - b_0$.

was positive or negative.[14] The results are presented for newly selected colleges in each period and for the resulting change in the cumulative portfolio. Cross-sectional estimates are presented in appendix A (apps. A–C are available online) for comparison.

A. Primary Specifications

In the case of students who take the exam one time, we estimate the following specification:

$$y_{it} = \beta_0 + \beta_1 s_i + \beta_2 z_{1i} + \beta_3 \mathbb{1}_{t=1} + \beta_4 s_i \mathbb{1}_{t=1} + \beta_5 z_{1i} \mathbb{1}_{t=1} + \epsilon_{it}, \quad (11)$$

where, for simplicity, we can think of s_i as students' PSAT scores (although we also include high school GPA, household income, gender, race, and geographic location), z_1 are SAT scores, and $\mathbb{1}_{t=1}$ is an indicator for the score report being sent after the scores are released. The outcomes y_{it} are the average characteristics of the colleges selected before or after the scores are released, with one observation per student per period. The coefficient β_4 represents the change in the coefficient on the PSAT after the SAT score is released, and β_5 represents the change in the coefficient on the SAT. The specification allows the PSAT and SAT to differ in their relative importance. An alternative specification measures the score shock as the difference between the SAT and PSAT, which generates a coefficient that is the average of the increased weight students place on newly revealed SAT scores and the decreased weight placed on PSAT scores.

For students who take the SAT twice, the specification is

$$\begin{aligned} y_{it} = {} & \beta_0 + \beta_1 s_i + \beta_2 z_{1i} + \beta_3 z_{2i} + \beta_4 \mathbb{1}_{t=1} + \beta_5 \mathbb{1}_{t=2} \\ & + \beta_6 s_i \mathbb{1}_{t=1} + \beta_7 z_{1i} \mathbb{1}_{t=1} + \beta_8 z_{2i} \mathbb{1}_{t=1} + \beta_9 s_i \mathbb{1}_{t=2} \\ & + \beta_{10} z_{1i} \mathbb{1}_{t=2} + \beta_{11} z_{2i} \mathbb{1}_{t=2} + \epsilon_{it}, \end{aligned} \quad (12)$$

where z_{1i} and z_{2i} are the first and second SAT scores. The coefficients β_7 and β_{11} represent the changes in the coefficients on the first and second SAT scores after each is released, and the coefficients β_6 and β_9 represent the corresponding changes for the PSAT. Two-time takers allow us to formally test whether the estimates of updating are biased upward or downward by score anticipation and time-varying strategies. Specifically, the coefficient β_8 on the second SAT score when only the first score is known is a measure of net bias. As shown in Section III, the difference $\beta_7 - \beta_8$ is π_1,

[14] Black and Smith (2006) detail the potential pitfalls of using a single measure of college quality, so we present a range of outcomes. Likewise, the use of ordinal variables such as test scores as an outcome has shortcomings (Bond and Lang 2013, 2014), so we verify that our results are robust to multiple polynomial transformations of our quality measure, including both highly left-skewed and highly right-skewed transformations.

Table 3
One-Time Takers: Portfolio Updating in Response to an SAT Score Shock

	New Colleges Added to Portfolio				Cumulative Portfolio	
Average SAT of Matriculates	(1)	(2)	(3)	Adjusted (4)	(5)	Adjusted (6)
PSAT score	.113***	.111***	.116***	.132***	.116***	.123***
	(.003)	(.003)	(.004)	(.004)	(.004)	(.003)
SAT score	.141***	.136***	.141***	.160***	.141***	.149***
	(.004)	(.004)	(.004)	(.005)	(.004)	(.004)
After SAT × PSAT score	−.022***	−.031***	−.029***	−.045***	−.012***	−.018***
	(.004)	(.005)	(.005)	.005	(.005)	(.004)
After SAT × SAT score	.072***	.070***	.071***	.053***	.029***	.021***
	(.004)	(.005)	(.005)	.006	(.005)	(.005)
Student controls (× post)	X	X	X	X	X	X
High school fixed effects (× post)		X				
Zip code fixed effects (× post)			X	X	X	X
Observations	258,036	258,036	258,036	258,036	258,036	258,036
R^2	.360	.339	.359	.358	.397	.394

NOTE.—This table presents the estimated effect of newly released SAT scores on a student's choice of college portfolio for alternative specifications. Columns 1–4 present the change in the average SAT of matriculating students at colleges selected before and after a student's score is released. Columns 5 and 6 present the change in the cumulative portfolio as a result. The estimates in cols. 4 and 6 have been adjusted to account for strategies that are correlated with student aptitude. Student controls include fixed effects for high school grade point average, race, gender, and household income. Each specification includes the interaction of the controls with an indicator for the postexam period. Note that only students who send score reports both before and after taking the SAT are included in the analysis. Standard errors are clustered at the zip code level. Bootstrapped errors are used in cols. 4 and 6 to account for the fact that the adjusted outcomes incorporate the estimates of Ω_t. PSAT = Preliminary SAT/National Merit Scholarship Qualifying Test.

*** Significant at the 1% level.

the unbiased estimate of updating in response to the SAT. We present specifications with and without adjusting y_{it} for time-varying strategies. As shown in appendix B, higher-ability students tend to exhibit larger differences in portfolio quality across information periods, which will generate upward bias in the estimates of updating.[15]

B. One-Time Takers: Updating

The estimates in table 3 reveal that students update their college portfolios in response to new information. In the preexam period, the coefficient on the PSAT reveals that a 100-point score difference is correlated with an 11-point difference in the selectivity of the colleges to which students send

[15] Note that the design is not sensitive to time-varying factors, such as performance in high school, participation in test preparation classes, or changes in motivation. This is because students choose their preexam college portfolios shortly before taking the SAT, whereas the postexam portfolios are selected after scores are released.

their scores. A similar positive correlation exists for the SAT. Students update their college selections to reflect their SAT scores after they are released and concurrently reduce their reliance on PSAT scores.[16] In column 1, which includes a rich set of student characteristics, the estimates indicate that a 100-point increase in SAT score causes a 7-point increase in the selectivity of colleges relative to the preexam period. This estimate is essentially unchanged when we include high school and zip code fixed effects in columns 2 and 3, in both cases interacting the fixed effects with a period indicator to account for changes in portfolio composition that are common to a school or community. Column 4 presents the preferred, strategy-adjusted specification. The resulting estimates are slightly smaller than those from the unadjusted specification, with a 5.3-point change in portfolio selectivity per 100-point SAT score shock. This implies that the unadjusted estimates are biased slightly upward, which is consistent with higher-ability students employing larger time-varying strategies. The adjusted estimates imply that a 1 standard deviation increase in SAT score leads to a 0.10 standard deviation increase in selectivity for newly added colleges.

The selectivity of the cumulative portfolio is important for understanding the extent to which score shocks are reflected in a student's choice set. The estimates in columns 5 and 6 indicate that students update in response to new information, but the overall changes are smaller because the colleges selected before the exam do not change. A 100-point SAT score shock changes the selectivity of colleges by about 3 points. That is, a 1 standard deviation shift in score changes the selectivity of the cumulative portfolio by 0.05 standard deviations. This high level of inertia over time challenges the assumption that academic qualifications are the primary determinants of college choice. That students select a large fraction of colleges before taking the SAT further reduces the alignment between portfolios and academic ability.

These causal estimates of updating are one-tenth of the magnitude found in a cross-sectional analysis. Specifically, after controlling for a rich set of covariates, a 100-point difference in SAT scores is correlated with a 22-point difference in portfolio selectivity, or 0.4 standard deviations. Thus, the degree of mismatch between student ability and college quality observed in cross-sectional data, which is high already, may understate the disconnect between academic qualifications and college preferences. This is surprising in light of the fact that, even if students know that scores are an imprecise measure of ability, the SAT plays a primary role in admission decisions and thus provides a strategic incentive for students to respond.

An alternative specification regresses portfolio quality before and after the scores are released on the gap between a student's SAT and PSAT

[16] Appendix C presents a specification that includes a continuous measure of GPA rather than GPA fixed effects. The resulting estimates reveal that students also rely less on their GPA after the SAT score is known.

scores. The results, presented in appendix C, reveal that a 100-point shock alters portfolio quality by 5 points, which is nearly identical to the primary specification. It is worth noting that attending the most selective college may be less desirable than attending one at the appropriate level.[17] Thus, we test whether students who experience larger score shocks, measured in terms of the absolute value of the gap, are more likely to send reports to appropriate "target" schools. The results provide little evidence that this occurs to a significant degree.

C. Two-Time Takers: Updating

The results for two-time takers presented in table 4 reveal that newly selected colleges in the period after each score is released reflect that score. The unadjusted estimate of the response to the first SAT score is about 5 points per 100, while the magnitude of the response to the second SAT score is about 8 points per 100. The small positive coefficient on the not-yet-released second score in columns 1–3 is the net bias generated by time-varying strategies and score anticipation. After adjusting for strategies in column 4, the estimates of updating are 4 and 6 points for the first and second exams, respectively. The remaining bias is close to 0, indicating that students do not accurately anticipate their scores and that the coefficient on the first score can be interpreted causally. As predicted by the model, students rely less on the PSAT after the first score is known and further reduce their reliance after the second score is known. Note that the effect of the first SAT score on colleges selected after the second score is revealed (measured relative to the baseline period) is small in magnitude. That is, students rely most heavily on new information when adjusting their portfolios.

The estimated effects of updating for the cumulative portfolio in columns 5 and 6 reveal that the first SAT score, not the second, affects the portfolio when only the first score has been released. A 100-point shock from the first SAT score causes students to adjust their portfolio by about 2 points. Note that the estimated bias is only 0.1 points, as indicated by the coefficient on the second score. After both exams are known to the student, the first and second scores have identical effects on the cumulative portfolio. Two results from this specification provide additional validation of the empirical design. First, if SAT scores are essentially random draws relative to a student's expectations, then they should be given equal weight before either score is

[17] For example, Loury and Gorman (1995) find that students with low SAT scores have lower probabilities of graduating when attending colleges with relatively higher SAT scores. Arcidiacono et al. (2014) find that minority college completion rates actually increased after an affirmative action ban that caused a shifting of minorities into less selective schools. Arcidiacono, Aucejo, and Hotz (2016) find that students with weaker academic preparation have higher returns to pursuing STEM (science, technology, engineering, and mathematics) fields at less selective schools than at more selective schools. For a comprehensive review, see Arcidiacono and Lovenheim (2016).

Table 4
Two-Time Takers: Portfolio Updating in Response to an SAT Score Shock

	New Colleges Added to Portfolio				Cumulative Portfolio	
Average SAT of Matriculates	(1)	(2)	(3)	Adjusted (4)	(5)	Adjusted (6)
PSAT score	.075***	.072***	.077***	.090***	.077***	.084***
	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)
SAT 1 score	.103***	.099***	.102***	.119***	.102***	.111***
	(.005)	(.005)	(.005)	(.006)	(.005)	(.006)
SAT 2 score	.110***	.109***	.127***	.104***	.109***	.119***
	(.004)	(.004)	(.004)	(.006)	(.004)	(.005)
After SAT 1 × PSAT score	−.016***	−.018***	−.019***	−.030***	−.010*	−.016***
	(.003)	(.005)	(.006)	(.006)	(.005)	(.005)
After SAT 1 × SAT 1 score	.048***	.055***	.053***	.041***	.026***	.021***
	(.004)	(.006)	(.006)	(.007)	(.006)	(.007)
After SAT 1 × SAT 2 score	.011***	.011*	.011*	−.004	.007	−.001
	(.004)	(.006)	(.006)	(.007)	(.006)	(.007)
After SAT 2 × PSAT score	−.035***	−.035***	−.038***	−.051***	−.017***	−.023***
	(.005)	(.006)	(.006)	(.006)	(.005)	(.005)
After SAT 2 × SAT 1 score	.019***	.016**	.017**	.000	.024***	.015**
	(.006)	(.007)	(.007)	(.008)	(.006)	(.007)
After SAT 2 × SAT 2 score	.079***	.078***	.079***	.062***	.024***	.014**
	(.005)	(.007)	(.007)	(.007)	(.006)	(.006)
Student controls (× post)	X	X	X	X	X	X
High school fixed effects (× post)		X				
Zip code fixed effects (× post)			X	X	X	X
Observations	334,506	334,506	334,506	334,506	334,506	334,506
R^2	.388	.377	.389	.387	.442	.437

NOTE.—This table presents the estimated effect of newly released SAT scores on a student's choice of college portfolio for alternative specifications. Columns 1–4 present the change in the average SAT of matriculating students at colleges selected before and after students' first and second SAT scores are released. Columns 5 and 6 present the change in the cumulative portfolio as a result. The estimates in cols. 4 and 6 have been adjusted to account for strategies that are correlated with student aptitude. Student controls include fixed effects for high school grade point average, race, gender, and household income. Each specification includes the interaction of the controls with indicators for each postexam period. Note that only students who send score reports both before and after taking the SAT are included in the analysis. Standard errors are clustered at the zip code level. PSAT = Preliminary SAT/National Merit Scholarship Qualifying Test.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

known. The estimated coefficients are 0.111 and 0.119 in period 0, and a formal test fails to reject that they are equal. Second, after both scores are known, each exam should be given equal additional weight for the cumulative portfolio. The coefficients for this period are very similar, with values of 0.015 and 0.014, and are not statistically different.

The estimates for two-time takers are similar to those for one-time takers in sign and magnitude. Nonetheless, to abstract from selection into retaking the exam, we merge one- and two-time takers and replicate the primary design. The results indicate that a 100-point test score shock causes a 5.5-point change in the average score of matriculating students at the colleges in the portfolio. This is consistent with the estimates generated separately for each group. A specification that regresses portfolio quality before and after each score is released on the gap between the score and a student's PSAT reveals similar estimates. Specifically, as shown in appendix C, the first and second scores generate increases in the selectivity of newly selected colleges of 3 and 6 points, respectively, and increases in the selectivity of the cumulative portfolio of 3 and 2 points.

Taken as a whole, the estimates reveal that students modestly update their college selections in response to large information shocks about the strength of their applications. The causal estimates of updating are a small fraction of the relationship observed in the cross section. For example, among two-time takers each 100 points on the second SAT is correlated with an 18-point difference in portfolio selectivity, which is five times the causal estimate for newly selected colleges and 10 times the estimate for the change in the cumulative portfolio. Thus, cross-sectional measures of student-college match may significantly overstate causal sorting on ability.

D. Alternative Measures of Portfolio Quality

Table 5 presents estimates of updating for alternative college characteristics. The results follow a pattern similar to those for selectivity and reveal several interesting insights about how students update. The least selective college chosen after a score is released does not appear to be very sensitive to the score shock, while the most selective college is. Specifically, a 100-point score shock changes the selectivity of the best college chosen by 12 points for one-time takers and 13 points for two-time takers, while the corresponding changes for the least selective college chosen are less than 2 points. These results suggest that students may send their scores to a set of safety schools regardless of their SAT performance and choose reach schools on the basis of their probability of admission. Score shocks generate modest changes in the fraction of private colleges to which students send their scores. A 100-point positive shock increases the fraction of private schools selected by about 1 percentage point for both one- and two-time takers. Likewise, the expected graduation rate of colleges selected is about 1 percentage point higher. These results imply that a 1 standard deviation shock in performance on the SAT results in a shift in the fraction of private colleges of 0.05 standard deviations and in the graduation rate of 0.10 standard deviations.

Students who receive positive shocks may be more likely to consider colleges that require greater investment because of higher tuition levels or greater distance from home. This could occur if, for example, students realize that their higher scores are more likely to result in admission to selective colleges or if they (and their parents) are more willing to invest in human

Table 5
Alternate Measures of Portfolio Quality

	Min SAT (1)	Max SAT (2)	Percent Private (3)	In-State Tuition (4)	Four-Year Graduation Rate (5)	Average Distance (6)	Lower Bound (7)
One-time takers:							
PSAT score	.097***	.126***	.021***	7.471***	.015***	.244***	.086***
	(.004)	(.004)	(.001)	(.298)	(.001)	(.016)	(.001)
SAT score	.127***	.147***	.020***	7.475***	.020***	.200***	.086***
	(.004)	(.004)	(.001)	(.304)	(.001)	(.016)	(.001)
After SAT × PSAT score	−.044***	−.017***	−.012***	−2.993***	−.005***	−.087***	−.002
	(.006)	(.006)	(.002)	(.444)	(.001)	(.023)	(.002)
After SAT × SAT score	.011*	.118***	.011***	4.093***	.010***	.115***	.014***
	(.006)	(.007)	(.002)	(.459)	(.001)	(.023)	(.002)
R^2	.212	.322	.081	.171	.291	.045	.223
Two-time takers:							
PSAT score	.070***	.082***	.017***	5.483***	.010***	.147***	.067***
	(.005)	(.005)	(.001)	(.362)	(.001)	(.018)	(.002)
SAT 1 score	.089***	.102***	.020***	6.735***	.015***	.159***	.084***
	(.006)	(.006)	(.002)	(.425)	(.001)	(.021)	(.002)
SAT 2 score	.109***	.100***	.010***	4.819***	.015***	.146***	.087***
	(.005)	(.005)	(.002)	(.411)	(.001)	(.020)	(.002)

After SAT 1 × PSAT score	−.017**	−.021***	−.004*	−1.164**	−.003***	−.032	−.008***
	(.007)	(.007)	(.002)	(.506)	(.001)	(.025)	(.002)
After SAT 1 × SAT 1 score	.042***	.057***	.007***	2.937***	.007***	.102***	.025***
	(.008)	(.008)	(.002)	(.600)	(.001)	(.029)	(.003)
After SAT 1 × SAT 2 score	.011	.010	.003	.977*	.001	.020	.007**
	(.008)	(.007)	(.002)	(.576)	(.001)	(.027)	(.003)
After SAT 2 × PSAT score	−.059***	−.022***	−.009***	−2.858***	−.006***	−.057**	−.013***
	(.007)	(.007)	(.002)	(.553)	(.001)	(.026)	(.002)
After SAT 2 × SAT 1 score	.024***	.017*	−.001	.449	.003**	.082***	.019***
	(.008)	(.009)	(.003)	(.645)	(.001)	(.030)	(.003)
After SAT 2 × SAT 2 score	.015**	.131***	.010***	4.036***	.011***	.066**	.028***
	(.008)	(.008)	(.003)	(.622)	(.001)	(.030)	(.003)
R^2	.241	.336	.095	.182	.315	.045	.389

NOTE.—This table presents the estimated effect of newly released SAT scores on a student's choice of college portfolio for alternative measures of quality. The top and bottom panels present the effects for one- and two-time takers, respectively. The outcomes in cols. 1 and 2 correspond to the lowest and highest average SAT score of matriculating students among colleges in the portfolio. Column 3 is the fraction of colleges in the portfolio that are private not-for-profit. Columns 4 and 5 consider the average in-state tuition and graduation rates for colleges in the portfolio. Column 6 presents the average distance from each student's home zip code to the colleges to which they send reports. Column 7 assumes that students who do not send score reports after the exam do not update. Student controls include fixed effects for high school grade point average, race, gender, and household income. Each control is interacted with indicators for the postexam periods. Standard errors are clustered at the zip code level. PSAT = Preliminary SAT/National Merit Scholarship Qualifying Test.

* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

capital when the probability of success seems greater. The results reveal that a 100-point positive score shock increases the mean tuition of colleges selected by $400, or 0.10 standard deviations per 1 standard deviation score shock. The average distance of selected colleges increases by 10 miles, or 0.04 standard deviations.

The estimates for each college characteristic reflect decreased importance placed on the PSAT after each SAT score is released. Of particular note for two-time takers is that, relative to the baseline period, the coefficients on the not-yet-released second SAT scores are generally not large or statistically significant, even without adjusting for strategies. Thus, the estimates are not significantly biased by score anticipation and time-varying strategies that are correlated with ability. Time-varying strategy-adjusted estimates for each outcome closely mirror the unadjusted estimates in both sign and magnitude (see app. B). As with the selectivity estimates, colleges chosen after the second score is revealed primarily incorporate this new information and not the first score, even though both scores are known and the estimates are relative to the preexam period.

Overall, updating as measured by a range of college characteristics provides clear causal evidence that students incorporate new information about their probability of admission and likelihood of success into their portfolio choices. Students incorporate information shocks into college choices in a way that affects the selectivity of reach colleges, public versus private composition, graduation rates, tuition, and proximity to home. However, the updating is an order of magnitude smaller than the size of the score shock and what is observed in the cross section, suggesting that high levels of inertia are present in college choice.

E. Extensive Margin Selection

Because reports must be sent after the exam in order to measure updating, the results are local to students who send more than the four free reports. While this is not a threat to the internal validity of the design, it does affect the interpretation of the estimates. As discussed in Section II, sending additional score reports appears primarily to be a function of household income and performance in high school and is only marginally sensitive to the magnitude of the score shock. Nonetheless, it is important to consider the implications for the estimates if those who send additional reports are more sensitive to new information than the population of SAT takers. Thus, we estimate the lower bound of student response by assuming that all students who do not send additional reports did not update their preferences. In practice, this is done by replacing missing postexam portfolios with preexam portfolios. The resulting estimates are presented in column 7 of Table 5. The estimates are mechanically smaller than the primary estimates but exhibit the same pattern of updating.

A specific subpopulation that may be especially prone to selecting out of sending additional reports are students who also take the ACT. These students may be less likely to use their SAT scores for admission and thus to reveal their entire portfolios. Thus, we replicate the design while restricting attention to states where the SAT is the most commonly taken entrance exam. The results for this sample are nearly identical to those for the full sample, with a 100-point score shock altering the selectivity of colleges selected by 6 points for one- and two-time takers (see app. C). Thus, it does not appear that the estimates are significantly biased by selection among ACT takers.

F. Heterogeneity in Updating

We examine whether responsiveness to scores varies with student ability or with the direction of the shock. To examine whether students with higher or lower baseline ability update more, we consider students who score below 1,000 on the PSAT (the median score) and students who score above 1,200 and thus are likely to be competitive for admission to more selective colleges and universities. To examine whether students respond differently to positive or negative shocks, we separately consider students whose SAT scores exceed or fall short of their PSAT scores.

The results in table 6 reveal that students with high baseline PSAT scores update more than students with low baseline scores. For one-time SAT takers, updating among high-ability students is 7.3 points per 100 points of score shock, relative to 5.8 points for lower-ability students. However, among two-time takers the differences are much more pronounced, with the higher-ability students exhibiting nearly double the level of updating. After the first and second SAT scores are released, students with high PSAT scores update their portfolios by 7.3 and 10.6 points, respectively, compared with only 3.5 and 6.5 points for students with low PSAT scores. A fully interacted model reveals that these differences are statistically significant.

This heterogeneity in baseline ability is consistent with high-ability students considering a wider array of college choices and perhaps being more strategic in terms of selecting colleges based on admissions probabilities. For example, lower-scoring students may consider only a fixed set of local public colleges and universities, while high-performing students may conduct regional or national searches. Students conducting broader searches are likely to have greater flexibility to alter which colleges they consider and thus exhibit greater levels of updating in response to score shocks. In addition to greater updating, students with higher baseline scores have larger coefficients on their PSAT and SAT scores in the preexam period, suggesting that they sort more strongly on ability even prior to the SAT. Results by gender and income do not reveal large differences across students from high- and low-income families (see app. C). Thus, the differences by student ability do not appear to be generated by differences in household resources.

Table 6
Updating by Ability and Type of Shock

	Baseline Ability		Type of Shock	
	PSAT <1,000 (1)	PSAT >1,200 (2)	Positive (3)	Negative (4)
One-time takers:				
PSAT score	.069***	.170***	.109***	.126***
	(.007)	(.008)	(.006)	(.010)
SAT score	.078***	.228***	.166***	.100***
	(.006)	(.008)	(.006)	(.010)
After SAT × PSAT score	−.018*	−.042***	−.032***	−.012
	(.010)	(.012)	(.009)	(.014)
After SAT × SAT score	.058***	.073***	.083***	.037**
	(.009)	(.011)	(.009)	(.015)
R^2	.119	.275	.385	.289
Two-time takers:				
PSAT score	.036***	.104***	.062***	.124***
	(.008)	(.009)	(.010)	(.012)
First SAT score	.058***	.157***	.117***	.063***
	(.008)	(.010)	(.010)	(.012)
Second SAT score	.086***	.134***	.126***	.077***
	(.008)	(.009)	(.009)	(.012)
After SAT 1 × PSAT score	−.017	−.014	−.027**	−.022
	(.011)	(.013)	(.013)	(.017)
After SAT 1 × SAT 1 score	.035***	.073***	.078***	.045***
	(.011)	(.013)	(.014)	(.016)
After SAT 1 × SAT 2 score	.004	.016	−.003	.018
	(.011)	(.013)	(.013)	(.017)
After SAT 2 × PSAT score	−.034***	−.041***	−.048***	−.044**
	(.012)	(.014)	(.014)	(.018)
After SAT 2 × SAT 1 score	.019	.008	.023	.038**
	(.012)	(.015)	(.016)	(.017)
After SAT 2 × SAT 2 score	.065***	.106***	.083***	.065***
	(.012)	(.014)	(.014)	(.018)
R^2	.158	.256	.402	.348

NOTE.—This table presents the estimated effect of newly released SAT scores on choice of college portfolio for students with low and high Preliminary SAT/National Merit Scholarship Qualifying Test (PSAT) scores and for students who experience positive and negative SAT score shocks. The top and bottom panels present the effects for one- and two-time takers, respectively. Each column presents the change in the average SAT score of matriculating students at colleges selected before and after a student's score is released. Each specification includes zip code fixed effects interacted with an indicator for the postexam periods. Note that only students who send score reports both before and after taking the SAT are included in the analysis. Standard errors are clustered at the zip code level.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Separating the results by whether students experience a positive or negative SAT score shock relative to their PSAT scores indicates that more updating occurs after a positive shock. For example, among one-time takers a positive 100-point shock alters portfolio selectivity 8.3 points, which is statistically significantly different from—and more than twice as large as—the effect of a negative shock. This suggests that students may deviate from a set of safety colleges only when they receive positive news and is consistent with our previous findings that information shocks primarily affect the quality of the most selective schools added to the portfolio.

V. Conclusion

The estimates in this paper reveal the role played by entrance exams in shaping college portfolios, shed light on how students update their human capital choices, and provide causal evidence for the inertia underlying student-college mismatch. We find consistent evidence that students adjust the colleges to which they send their SAT score reports in response to new information about the strength of their applications. Positive information shocks generated by SAT scores cause students to choose more selective colleges that charge higher tuition, have higher graduation rates, and are located farther from home. However, the magnitude of the responses is much too small to close the unexplained gaps between students who appear to have similar academic qualifications. These results suggest that it is difficult to change students' college choices even after providing them with new, highly relevant information about their probability of admission and likelihood of success. The results contribute revealed preference-based evidence to a growing literature that attempts to understand how students update their human capital choices and why college mismatch occurs.

A point of significant policy interest is identifying ways to close the gap in outcomes between students from higher- and lower-income households. College entrance exams are taken by nearly all students considering a 4-year college. This study suggests that the SAT can play a role in bringing college portfolios into alignment with academic performance. However, there is a significant amount of inertia in portfolio choice that must be overcome. The predetermined nature of college choice for many students could be due to nonacademic factors, such as poor counseling, geographic preferences, price sensitivity, and loyalty to colleges attended by relatives and friends. Alternatively, students may not be skilled at translating SAT performance into college admission predictions. The magnitude of student updating is likely to vary with both the timeliness and the salience of new information about college choice. These findings may help to improve the way in which students, parents, and school counselors receive and respond to critical information in the application process.

References

Abramitzky, Ran, and Victor Lavy. 2014. How responsive is investment in schooling to changes in redistributive policies and in returns? *Econometrica* 82, no. 4:1241–72.

Altonji, Joseph G. 1993. The demand for and return to education when education outcomes are uncertain. *Journal of Labor Economics* 11, no. 1:48–83.

Altonji, Joseph G., Erica Blom, and Costas Meghir. 2012. Heterogeneity in human capital investments: High school curriculum, college major, and careers. *Annual Review of Economics* 4:185–223.

Altonji, Joseph G., and Charles R. Pierret. 2001. Employer learning and statistical discrimination. *Quarterly Journal of Economics* 116, no. 1:313–50.

Andrews, Rodney J., Vimal Ranchhod, and Viji Sathy. 2010. Estimating the responsiveness of college applications to the likelihood of acceptance and financial assistance: Evidence from Texas. *Economics of Education Review* 29, no. 1:104–15.

Arcidiacono, Peter. 2005. Affirmative action in higher education: How do admission and financial aid rules affect future earnings? *Econometrica* 73, no. 5:1477–524.

Aricidiacono, Peter, Esteban Aucejo, Patrick Coate, and V. Joseph Hotz. 2014. Affirmative action and university fit: Evidence from Proposition 209. *IZA Journal of Labor Economics* 3, no. 7:1–29.

Arcidiacono, Peter, Esteban Aucejo, and V. Joseph Hotz. 2016. University differences in graduation minorities in STEM fields: Evidence from California. *American Economic Review* 106, no. 3:525–62.

Arcidiacono, Peter, Esteban Aucejo, Arnaud Maurel, and Tyler Ransom. 2016. College attrition and the dynamics of information revelation. NBER Working Paper no. 22325, National Bureau of Economic Research, Cambridge, MA.

Arcidiacono, Peter, Patrick Bayer, and Aurel Hizmo. 2010. Beyond signaling and human capital: Education and the revelation of ability. *American Economic Journal: Applied Economics* 2, no. 4:76–104.

Arcidiacono, Peter, V. Joseph Hotz, and Songman Kang. 2012. Modeling college major choices using elicited measures of expectations and counterfactuals. *Journal of Econometrics* 166, no. 1:3–16.

Arcidiacono, Peter, Shakeeb Khan, and Jacob L. Vigdor. 2011. Representation versus assimilation: How do preferences in college admissions affect social interactions? *Journal of Public Economics* 95, no. 1:1–15.

Arcidiacono, Peter, and Michael Lovenheim. 2016. Affirmative action and the quality-fit tradeoff. *Journal of Economic Literature* 54, no. 1:3–51.

Attanasio, Orazio P., and Katja M. Kaufmann. 2009. Educational choices, subjective expectations, and credit constraints. NBER Working Paper no. 15087, National Bureau of Economic Research, Cambridge, MA.

Avery, Christopher, and Thomas J. Kane. 2004. Student perceptions of college opportunities: The Boston COACH Program. In *College choices: The economics of where to go, when to go, and how to pay for it*, ed. Caroline M. Hoxby, 355–94. Chicago: University of Chicago Press.

Behrman, Jere R., Mark R. Rosenzweig, and Paul Taubman. 1996. College choice and wages: Estimates using data on female twins. *Review of Economics and Statistics* 78, no. 4:672–85.

Bettinger, Eric, Bridget Terry Long, Philip Oreopoulos, and Lisa Sanbonmatsu. 2012. The role of application assistance and information in college decisions: The H&R Block FAFSA experiment. *Quarterly Journal of Economics* 127, no. 3:1205–42.

Black, Dan A., and Jeffrey A. Smith. 2006. Estimating the returns to college quality with multiple proxies for quality. *Journal of Labor Economics* 24, no. 3:701–28.

Bond, Timothy N., and Kevin Lang. 2013. The evolution of the black-white test score gap in grades K–3: The fragility of results. *Review of Economics and Statistics* 95, no. 5:1468–79.

———. 2014. The sad truth about happiness scales. NBER Working Paper no. 19950, National Bureau of Economic Research, Cambridge, MA.

Bound, John, Brad Hershbein, and Bridget Terry Long. 2009. Playing the admissions game: Student reactions to increasing college competition. *Journal of Economic Perspectives* 23, no. 4:119–46.

Bulman, George. 2015. The effect of access to college assessments on enrollment and attainment. *American Economic Journal: Applied Economics* 7, no. 4:1–37.

Card, David, and Alan B. Krueger. 2005. Would the elimination of affirmative action affect highly qualified minority applicants? Evidence from California and Texas. *Industrial and Labor Relations Review* 58, no. 3: 414–34.

Carrell, Scott, and Bruce Sacerdote. 2017. Why do college-going interventions work? *American Economic Journal: Applied Economics* 9, no. 3: 124–51.

Chade, Hector, Gregory Lewis, and Lones Smith. 2014. Student portfolios and the college admissions problem. *Review of Economic Studies* 81, no. 3: 971–1002.

Cohodes, Sarah R., and Joshua S. Goodman. 2014. Merit aid, college quality, and college completion: Massachusetts' Adams Scholarship as an in-kind subsidy. *American Economic Journal: Applied Economics* 6, no. 4: 251–85.

Dillon, Eleanor, and Jeffrey Smith. 2017. Determinants of the match between student ability and college quality. *Journal of Labor Economics* 35, no. 1:45–66.

Dizon-Ross, Rebecca. 2017. Parents' beliefs about their children's academic ability: Implications for educational investments. Working paper.

Epple, Dennis, Richard Romano, and Holger Sieg. 2006. Admission, tuition, and financial aid policies in the market for higher education. *Econometrica* 74, no. 4:885–928.

Farber, Henry S., and Robert Gibbons. 1996. Learning and wage dynamics. *Quarterly Journal of Economics* 111, no. 4:1007–47.
Fu, Chao. 2014. Equilibrium tuition, applications, admissions, and enrollment in the college market. *Journal of Political Economy* 122, no. 2:225–81.
Goodman, Sarena. 2016. Learning from the test: Raising selective college enrollment by providing information. *Review of Economics and Statistics* 98, no. 4:671–84.
Hoekstra, Mark. 2009. The effect of attending the flagship state university on earnings: A discontinuity-based approach. *Review of Economics and Statistics* 91, no. 4:717–24.
Hoxby, Caroline, and Sarah Turner. 2014. Expanding college opportunities for high-achieving, low-income students. Stanford Institute for Economic Policy Research Discussion Paper no. 12–014.
Hoxby, Caroline M., and Christopher Avery. 2013. The missing "one-offs": The hidden supply of high-achieving, low-income students. *Brookings Papers on Economic Activity*, no. 1:1–65.
Hurwitz, Michael, Jonathan Smith, Sunny Niu, and Jessica Howell. 2015. The Maine question: How is 4-year college enrollment affected by mandatory college entrance exams? *Educational Evaluation and Policy Analysis* 37, no. 1:138–59.
Jacob, Brian A., and Tamara Wilder Linkow. 2011. Educational expectations and attainment. In *Whither opportunity*, ed. Greg Duncan and Richard Murnane. New York: Sage.
Jensen, Robert. 2010. The (perceived) returns to education and the demand for schooling. *Quarterly Journal of Economics* 125, no. 2:515–48.
Kahn, Lisa B., and Fabian Lange. 2014. Employer learning, productivity, and the earnings distribution: Evidence from performance measures. *Review of Economic Studies* 81:1575–613.
Klasik, Daniel. 2013. The ACT of enrollment: The college enrollment effects of state-required college entrance exam testing. *Educational Researcher* 42:151–59.
Lange, Fabian. 2007. The speed of employer learning. *Journal of Labor Economics* 25, no. 1:1–35.
Long, Mark C. 2004. College applications and the effect of affirmative action. *Journal of Econometrics* 121, no. 1:319–42.
Loury, Linda Datcher, and David Garman. 1995. College selectivity and earnings. *Journal of Labor Economics* 13, no. 2:289–308.
Manski, Charles. 1989. Schooling as experimentation: A reappraisal of the post-secondary drop-out phenomenon. *Economics of Education Review* 8, no. 4:305–12.
McDuff, DeForest. 2007. Quality, tuition, and applications to in-state public colleges. *Economics of Education Review* 26, no. 4:433–49.

Oreopoulos, Phillip, and Reuben Ford. 2016. Keeping college options open: A field experiment to help all high school seniors through the college application process. NBER Working Paper no. 22320, National Bureau of Economic Research, Cambridge, MA.

Pallais, Amanda. 2015. Small differences that matter: Mistakes in applying to college. *Journal of Labor Economics* 33, no. 2:493–520.

Papay, John P., Richard J. Murnane, and John B. Willett. 2016. The impact of test score labels on human-capital investment decisions. *Journal of Human Resources* 51, no. 2:357–88.

Rockoff, Jonah E., Douglas O. Staiger, Thomas J. Kane, and Eric S. Taylor. 2012. Information and employee evaluation: Evidence from a randomized intervention in public schools. *American Economic Review* 102, no. 7:3184–213.

Smith, Jonathan. 2016. The sequential college application process. Working paper.

Smith, Jonathan, Matea Pender, and Jessica Howell. 2013. The full extent of student-college academic undermatch. *Economics of Education Review* 32:247–61.

Stange, Kevin M. 2012. An empirical investigation of the option value of college enrollment. *American Economic Journal: Applied Economics* 4, no. 1:49–84.

Stinebrickner, Todd, and Ralph Stinebrickner. 2012. Learning about academic ability and the college dropout decision. *Journal of Labor Economics* 30, no. 4:707–48.

———. 2013. A major in science? Initial beliefs and final outcomes for college major and dropout. *Review of Economic Studies* 81, no. 1:426–72.

Wiswall, Matthew, and Basit Zafar. 2015. Determinants of college major choice: Identification using an information experiment. *Review of Economic Studies* 82, no. 2:791–824.

Zafar, Basit. 2011. How do college students form expectations? *Journal of Labor Economics* 29, no. 2:301–48.