The Sequential College Application Process

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Abstract

To demonstrate the sequential nature of the college application process, this paper analyzes the evolution of applications among high-achieving low-income students through data on the exact timing of SAT score sends. I describe at what point students send scores to colleges and which score sends ultimately become applications, resulting in three main points. First, score sends are not synonymous with applications, rather, only 62 percent of score sends in this sample turn into applications. Second, the conversion from score send to application is non-random as it relates to college characteristics: score sends are more likely to convert into applications when they are to colleges with lower tuition, higher graduation rates, and relatively near a student's home. Third, the timing of score sends is related to the probability of becoming an application whereby score sends sent relatively early are least likely to become applications. These facts imply that there is room for improvement when modeling the application process and in addition, the timing of an intervention or policy may be critical to its success.

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1. Introduction

Researchers typically treat the college application portfolio as a simultaneous choice problem, whereby students make a single decision at one point in time- choose the utility maximizing set of colleges from all possible sets, subject to a budget constraint. In reality, the application portfolio evolves over the course of students' high school careers, if not earlier, as they gather information about colleges, their own ability, and their preferences. For example, students may know from a young age that they want to apply to their state flagship or a school with a prominent sports team (Pope and Pope, 2009) and then they build a portfolio around that single college, only to change the portfolio once they learn their SAT scores (Bond et al., 2017).

This simple example raises two lines of inquiry regarding the sequence of applications and education research and policy. First, assuming some colleges enter the application portfolio earlier than others, how do policies and interventions impact later applications, conditional on there already being some applications in the portfolio? Theoretical and structural models on education policies, such as affirmative action (e.g. Arcidiacono, 2005) or financial aid (e.g. Epple, Romano, and Seig, 2006), do not address this issue.[1] Since students are often counseled to apply to a "balanced portfolio," policies may only be effective at changing application behavior if the early applications are of a certain type (e.g., low or high quality; safety or reach). Second, can policies and interventions administered at different times yield different results by virtue of changing the sequence of applications? Hoxby and Turner (2013) show that high-achieving low-income students' applications can be changed with a low-cost informational intervention. An earlier intervention may change the applications sent the earliest, which by

[1] These simplifying assumptions are for justifiable reasons related to data limitations and model tractability. For more examples, see Manski and Wise (1983), Arcidiacono (2005), Epple, Romano, and Seig (2006), Chade and Smith (2006), Howell (2010), Chade, Lewis, and Smith (2014), and Fu (2014).

virtue of the portfolio consideration, may indirectly impact the later applications. Despite the potential valuable information for education policy, we know almost nothing about the sequence of applications and the portfolio building process. This paper starts to fill that knowledge gap.

To demonstrate the sequential nature of the application process, this analysis makes use of SAT score sends. Students who apply to four-year colleges are typically required to send official documentation of their SAT or ACT scores, known as score sends, which have been argued to be good proxies for applications (Card and Krueger, 2005; Pallais, 2015) and "about 90 percent of first-time, degree-seeking students enrolling at traditional BA/BS granting institutions are either required or recommended to submit official college entrance exam scores with college applications" (Hurwitz et al., 2016). The data I use offer two novelties to the often used score send data. First, through College Board's administrative data, I observe the exact date the score sends are requested- many of which are as early as junior year in high school and many of which are close to application deadlines (well into senior year). Second, through a survey of high-achieving low-income students, I learn which score sends become applications. Compared to their high-income peers, high-achieving low-income students are less likely send college applications or enroll in colleges that are commensurate with their academic credentials (Hoxby and Avery, 2012; Smith et al., 2013). These students also show improvements in the application process when given an informational and financial intervention (Hoxby and Turner, 2013), making them both a disadvantaged population and population receptive to change and in all, worthy of further research.[2] Combined, these data shed light on the colleges these academically qualified students consider, at what point in time they consider the colleges, and which ones ultimately become applications.

[2] There are also numerous organizations who aim to serve this population, including the Jack Kent Cooke Foundation and the College Board's Access 2 Opportunity program, to name a few.

There are three main findings from analyses of these data. First, score sends are not applications. Only 62 percent of score sends in this sample turn into applications. In the concurrent working paper most similar to this one, Orzeck and Minicucci (2017) find that 72.4 percent of score sends convert into applications. They have the advantage of seeing the entire set of score sends and applications to a set of colleges but the disadvantage of not seeing a student's complete set of score sends (or timing). Second, the conversion from score sends to applications is non-random as it relates to college characteristics. For example, I find that score sends to colleges with higher graduation rates and lower tuition, two desirable attributes, are more likely to convert into applications, as are those to colleges that are near home, private, and have a larger enrollment. These last few attributes are not objectively desirable but rather, demonstrate students' preferences, all else equal. These first two findings suggest that past and future research that use score sends as outcomes should consider how treatments impact the types of scores sends and whether these are likely to convert to applications.

Third, I test whether the sequence of decision making relates to the probability of application conversion. To test this, I write down a theoretical framework for how students sequentially choose applications and estimate two reduced-form models (with different assumptions) that exploit the timing of score sends and College Board score sending policies that elicit the evolution of students' application portfolio.[3] These data were previously unavailable and highlight student decision making over time. I find that score sends that are free upon SAT registration and those chosen relatively early are not likely to convert into college applications,

[3] The two models make assumptions about whether each application decision is independent of one another or whether they are jointly determined. I discuss the weaknesses of each model but they provide the benefit of tackling one problem with two different estimation strategies.

suggesting that students learn about themselves or colleges in a way that changes their ultimate portfolio.

Finally, I investigate how these variables associate with the probability of enrollment. This is similar in spirit to Long (2004), who examines the student and college characteristics that relate to enrollment and how they have changed over the decades. This paper adds to her work with the novel timing variables. I find that free score sends are more likely to convert to enrollment than non-free score sends, despite the fact that they are less likely to convert to applications. This result highlights the complicated nature of the application process and suggests that students' portfolios start with some colleges that they highly preferred and are well thought out but at the same time, include colleges that are not well thought out and never convert into an application.

Combined, these findings contribute to several strands of literature regarding college choice. First, as mentioned, theoretical and structural models of college applications and enrollment could be enhanced to include the sequencing of events to better mirror the behavior observed in this work. Data limitations often preclude this option, but the simplifying assumptions should be noted and considered. Second, this paper relates to the sizeable number of papers that use score sends as proxies for applications in the outcome for policy analysis.[4] There is nothing inherently wrong with these papers or using score sends in this manner but given the non-random conversion of score sends to applications by college characteristics and timing implies that previous research should consider which score sends the policy induced (and when) and whether that will ultimately translate into applications. For example, a policy that induces an additional free score send in a student's junior year of high school to a college with a

[4] Most of my papers fall under this category, as do Toutkoushian (2001), Long (2004b), Card and Krueger (2005), Pallais (2015), Hurwitz et al (2016).

low graduation rate that is far from home is unlikely to convert to an application. Consequently, score sends should more accurately be described as elements of a choice set prior to applications.

Finally, this paper follows a long line of research on the college application process. This paper illuminates the sequencing by quantifying what has previously been described in generalities: such as the "college destination" process (Radford, 2013; Hossler and Gallagher, 1987) or the "application gauntlet" (Klasik, 2012). The majority of the vast literature on the application process is about the determinants of applications, ranging from the impacts of rankings (e.g., Monks and Ehrenberg, 1999; Luca and Smith, 2013; Alter and Reback, 2014; Bowman and Bastedo, 2009), counseling (see Avery, Howell, and Page, 2014 for an overview), geographic remoteness (Hoxby and Avery, 2013), affirmative action type policies (e.g., Long, 2004b; Black et al 2015), income (e.g., Toutoushian, 2001; Griffith and Rothstein, 2009), general sets of correlates (e.g., Weiler, 1994; DesJardins et al., 1999), and a host of barriers (Page and Scott-Clayton, 2015). The sequencing of application decisions is not central (or even periphery) to any of these papers but it does lie in the subtext. For example, many of these papers rely on a change in policy or information, which occur at a point in time and consequently impact students' applications. But which applications are they impacting, early or late and good or bad fits, and what if the policy occurred at a different time?

The paper proceeds as follows: Section 2 describes the data, which include College Board administrative data on SAT-takers and their score sends, along with the survey of a select sample to determine applications. Section 3 describes the theoretical framework and the corresponding estimation strategies. Section 4 presents the results and Section 5 concludes.

2. Data

The data come from three primary sources: College Board administrative data, a survey of high achieving low-income students conducted by the College Board, and the Integrated Postsecondary Educational Data System (IPEDS).

2.1. College Board Data

The main data come from SAT-takers in the graduating high school class of 2014. The College Board administers the SAT, one of the two major college entrance exams in the U.S., to approximately 1.7 million students in each high school cohort. In doing so, the College Board maintains a database of students' SAT scores, which range from 200 to 800 on each of the math and critical reading sections with a composite score ranging from between 400 and 1600.[5] At the time of SAT registration, students complete a questionnaire that includes basic demographics, such as race, gender, parental income and education, along with the student's home zip code.

Students who apply to colleges are frequently required to send official documentation of their SAT scores, known as score sends.[6] Between the point of SAT registration and for 9 days after taking the exam, students can designate up to four colleges to receive their SAT scores at no additional cost. After that period, additional score sends can be sent at any time for $11.25 each. Low-income students who received an SAT fee waiver from their guidance counselor are eligible for four additional "flexible" score sends that are free and can be used at any time during high school.[7] The data contain the exact colleges to which students send their scores along with

[5] There is a writing section out of 800 points as well, but the writing section is now optional for students. I use math and critical reading for better comparability with older cohorts and future cohorts.
[6] Score sends are infrequently sent to non-postsecondary institutions, such as scholarship organizations (e.g., National Merit) and athletic programs (e.g., NCAA). The 6 percent of these score sends are excluded from all analyses.
[7] Hurwitz et al. (2016) show that this policy increases the number of score sends and improves enrollment and completion rates.

the exact date they request the score send.[8] If students take the SAT multiple times, they have the option to send only the most favorable score but I cannot observe this information, just whether at least one score was sent to a college. Finally, I exclude the handful of students who first take the SAT prior to high school. Approximately 98.5 percent of students take the SAT for the first time sometime after their freshman year of high school and excluding the 1.5 percent does not impact future results.

2.2. National Student Clearinghouse

The College Board merges their administrative data to the National Student Clearinghouse (NSC). As of 2015, over 3,600 postsecondary institutions participate in NSC, which collects postsecondary enrollment information on more than 98 percent of students enrolled in public and private colleges within the United States. Due to data privacy laws and potential complications with student matching, the actual NSC coverage may be a bit lower than the advertised 98 percent rate (Dynarski, Hemelt, & Hyman, 2015). These data provide a near complete view of the colleges that SAT-takers ultimately enroll in.

2.3. Application Data - Survey of High Achieving Low-Income Students

The College Board conducted a survey of high-achieving low-income students (HALIs) at the end of their senior year to learn more about their application and enrollment process. High-achieving students were measured by either PSAT or SAT scores and generally have composite SAT scores of at least 1250.[9] Potential low-income students were identified by a proprietary algorithm based on geocoded data that identifies students with a high probability of living with

[8] Free score sends are often requested at the time of registration but fulfilled several months later, after the SAT is taken and scored. I rely on the request date, not fulfill date.

[9] Formally, the students had to either score a 125 on their PSAT (maximum of scores across attempts) or a 1250 on their SAT (using the sum of the maximum scores on each section).

families earning less than $40,000 annually. Students were asked to list up to ten colleges to which they applied and also the total number of applications if it exceeded ten.[10]

The survey completers serve as the analytic sample because I have complete information on score sends, applications, and enrollment. Approximately 20 percent of HALIs were sent the survey and approximately 30 percent of those invited to participate completed the survey, which translates to six percent of all HALIs completing the survey.[11] The survey design oversampled racial minorities, which is reflected in the summary statistics of survey takers and all HALIs in Appendix Table 1. However, survey takers and HALIs are extremely similar on academic credentials and aspirations, including high school GPA, SAT scores, number of SAT attempts, and perhaps most critically, number of score sends. It is possible that survey taking is correlated with some of the variables of primary interest, which can induce bias, but data limitations require a selection on observables assumption. In some analyses, I re-weight the sample to reflect the true population of SAT-taking HALIs. It is important to note that these data do not represent all SAT takers, who differ substantially from HALIs and the analytic sample, as demonstrated in the rightmost panel of Appendix Table 1. However, the academic characteristics of the HALIs are not that different than those of all high-achieving students, not just low-income students.

Also, approximately 20 percent of applications cannot be matched to a score send. This may occur because the student also took the ACT and sent the ACT score instead of the SAT score or if the student did not send any test scores, perhaps because the college is test optional. The ACT issue is assuaged in robustness checks on students who certainly submitted the SAT. The latter issue is likely small, since the sample of students are high-achieving, as measured by

[10] Exceeding 10 applications was rare and I test the sensitivity of my results to not having complete application data.
[11] The exact percent of students invited to participate in the survey was lost, including exactly which students were invited.

exam scores, and only students with relatively low scores tend not to submit (Conlin et al., 2013).

2.4. Integrated Postsecondary Educational Data System

The Integrated Postsecondary Educational Data System (IPEDS) includes annual data on over 7,000 colleges in the U.S. I use the most recently reported IPEDS data available as of July 2015, which, depending on the variable, are usually lagged a few years.[12] For each score send across all students, I append a variety of college-level variables from IPEDS including: average SAT of enrolled students, six-year graduation rate, in-state and out-of-state tuition and fees (listed tuition, not net tuition), public or a flagship state institution flag, and the first-time full-time enrollment count. In addition, I determine in-state status for and calculate distance to each college among a student's score sends using latitude and longitude of each college relative to student's home zip code.

2.5. Summary Statistics

Summary statistics for the 1,441 survey respondents are presented in Table 1. Almost 52 percent of the students are male and there are near equal proportions of white, black, Hispanic, and Asian students, reflecting the survey design. Since the College Board's survey was administered to high-achieving students, it is not surprising that their average high school GPA is close to 4.0 and the average SAT is 1329. Students typically took the SAT twice, which results in an average of almost seven score sends. On average, students report submitting just over four applications, which demonstrates that not all score sends convert into applications. Finally, students send their SAT scores to colleges where the average SAT of enrolled students is 1278 and where the colleges are an average of 567 miles from home.

[12] The variables are from the 2013 collection year, change very little from year to year, and are similar to what students would see when considering an application.

Summary statistics at the score send level appear in the left panel of Table 2. Among the over 10,000 observed score sends, only 62 percent turn into applications. Students send SAT scores to very selective colleges, as evidenced by the high average SAT scores of enrolled students and the graduation rates of these colleges. Many of the score sends are to expensive institutions (at least based on sticker price) but in reality, many of these low-income students would be eligible for generous financial aid packages from these well-resourced institutions. On average, students are sending scores to colleges that are 668 miles from home. Finally, scores sends go to instate public flagships 6.7 percent of the time, instate public non-flagships 17.6 percent of the time, instate privates 15 percent of time, and a disproportionate 47.2 percent of the time to out of state private colleges. The large fraction going to private colleges demonstrates the options these HALIs have that students with lower scores do not.

Table 2 also presents information on the timing of score sends. Approximately one-third of score sends are "free," which means they are chosen at the time of an SAT registration and therefore typically are sent earlier than non-free score sends. 11.7 percent of score sends were sent prior to the spring of junior year, suggesting that numerous students took the SAT relatively early and they started considering colleges well in advance of application deadlines. Another 8.5 percent of scores sends are sent in the spring of junior year- the most frequent season these students first took the SAT. Almost no score sends are sent in the following summer and in contrast, approximately 41 percent of score sends are sent during the fall of one's junior year when almost all these students take the SAT, often for the second time, and some early application deadlines lapse.

Whether these measures of sequencing matter is an important contribution of this paper and preliminary evidence is presented in Figure 1. Time is plotted on the horizontal axis, month by month, and counts of score sends and applications are on the vertical axis. For example, in March 2013, 369 score sends are sent but only 183 of those turned into applications (note that the applications are not sent in March 2013). In contrast, in December 2013, a time where college applications deadlines are looming, we see 2,234 score sends of which, 1,398 convert into applications. Regardless of when the students send the scores, some of the score sends do not convert to applications. I will explicitly examine the relationship between time and conversion rates, conditional on a host of covariates, in the empirical section.

3. Theoretical Framework and Empirical Strategy

I assume students choose a set of colleges to apply to that maximizes their expected utility subject to a budget constraint. Prior to that, students sequentially gather information on colleges and their own ability and preferences. This departure from typical static models is supported by the above descriptive statistics that show how score sends are sent at different time periods. These general ideas are formalized below.

Students start at time $t=0$ with no information about the set of S colleges in the marketplace. They begin to consider the college application process at time $t=1$ long before applications are due at time $t=T$. At each time period *t*, student *i* has an information set Ω_{it} where $\Omega_{it} \subseteq \Omega_{it+1}$ Let $\Omega_{it} = [X_{it}, Z_{it}]$, which includes a vector of details regarding the student's abilities and preferences X_{it}, such as SAT scores, and characteristics of colleges and the market place Z_{it}, such as the existence of a college.[13] The latter is informed by the empirical evidence

[13] Alternatively, Z_{it} could include all colleges and attributes but assign zero weight (or infinitely negative utility) to the attributes or colleges to which the students are unaware- ensuring that the colleges will never be chosen.

that students do not have full information on the thousands of colleges across the country (e.g., Dillon and Smith, 2017).

With the information set Ω_{it}, students form a set of colleges they are considering, C_{it}. Note that C_{it} is a vector of colleges and I assume that, as time progresses, the choice set can only grow such that mathematically $C_{it} \subseteq C_{it+1} \subseteq C_{iT} \subseteq S$.[14] Let the colleges in the choice set at time *t* be denoted $C_{it} = [s_{it1}, s_{it2}, ..., s_{itk}, ..., s_{itK}]$ such that k indexes each of the K colleges in the set. College k can be described as follows: $s_k = s(z_k, \tau_k)$ where z_k are the characteristics of the college and τ_k describe when colleges enter the choice set.

The students' optimization problem is to choose a portfolio of college applications, P_{iT} at time *T*, conditional on the contemporaneous information set Ω_{iT} and the choice set C_{iT}, where $P_{iT} \subseteq C_{iT}$.

Below, I consider two different optimization problems a student may face, which also dictates the most suitable estimation strategy:

Model 1 - Students independently choose whether to apply to each college in their choice set.

Model 2 - Students jointly choose which colleges to apply to from among the colleges in the choice set.

Model 1 rests on the strong assumption that applications are chosen independently of one another. The model has the merits of an easily interpretable estimation strategy and has been used in previous research (e.g., Hoxby and Avery, 2012; Black et al., 2015). Model 2 relaxes the

[14] Students can down weight a college such that it is never going to become an application but I still assume it is in the choice set, just with less or even zero weight.

strong assumption and allows for application decisions to depend on one another, despite being more complicated to estimate and interpret.

Next, I discuss the theoretical framework for each model and the corresponding assumptions, weaknesses, and estimation strategies.

3.1. Model 1 – Independent Applications

For each college *k* in the final choice set C_{iT}, student *i* must decide whether to send an application. An application to the college yields utility[15]:

$$U(s_{ikT} \mid \Omega_{iT}) = U(z_{ikT} \mid X_{iT}, Z_{iT}, \tau_{ik}) \tag{1}$$

Assume a constant marginal cost of an application,[16] denoted θ, which includes time and financial costs. With a budget constraint of ω_i, she can only apply to $\overline{K} \leq K$ colleges such that:

$$\theta \cdot \overline{K} \leq \omega_i \tag{2}$$

Therefore, a student applies to a college if it yields the most utility among all colleges in her choice set C_{iT} or mathematically:

$$U(s_{ikT} \mid \Omega_{iT}) \geq U(s_{ijT} \mid \Omega_{iT}) \text{ for all } j \neq k \tag{3}$$

and if the utility is greater than the marginal cost:

$$U(s_{ikT} \mid \Omega_{iT}) \geq \theta \tag{4}$$

If the college with the highest utility does not end in an application, the student does not consider applying to the less preferred colleges. If the student does apply to the most preferred college, then the student considers the next most preferred college, say, *m*:

$$U(s_{ikT} \mid \Omega_{iT}) \geq U(s_{imT} \mid \Omega_{iT}) \geq U(s_{ijT} \mid \Omega_{iT}) \text{ for all } j \neq k \neq m \tag{5}$$

[15] The utility from an application can be thought of as the expected utility, net of the probability of admission.
[16] Applications likely do not have a constant marginal cost. In addition, there likely exist student-college specific application costs. I assume constant marginal costs for model simplicity and data limitations.

and applies if equation (4) holds for college *m*. The process continues for all colleges in the choice set until the budget constraint is binding, the utility of the next preferred application is outweighed by the marginal cost, or there are no more colleges in the choice set.

It should be emphasized that the decision to apply to one college is not dependent on the other colleges in the choice set. The primary advantage of this assumption is the simplification of the estimation strategy and interpretation that I describe below, which is similar to Hoxby and Avery (2012) and Black et al. (2015).

3.1.1. Estimation

Assuming linearity, equation (1) can be rewritten as follows:

$$U(s_{ikT} \mid \Omega_{iT}) = \alpha + \beta z_{ikT} + \gamma X_{iT} + \varepsilon_{ik} \qquad (6)$$

I estimate whether the college gives sufficiently large utility to warrant an application. As is usually the case, I do not observe the latent variable but rather, I only observe whether the student applies to the college, denoted A_{ik}. Let $A_{ik} = 1$ if the student applies the college and $A_{ik} = 0$ if not, such that I can estimate the probability of an application using OLS with the following specification:

$$P(A_{ik} = 1 \mid \Omega_{iT}) = \alpha + \beta z_{ikT} + \gamma X_{iT} + \varepsilon_{ik} \qquad (7)$$

In practice, the main specification uses a student fixed effect, such that student invariant characteristics in X_{iT} are excluded other than the interaction of z_{ikT} and X_{iT}, such as distance from home or whether the college is in the same state as the student.[17] The fixed effects models

[17] Logit models, as opposed to OLS, and conditional logit models, as opposed to student fixed effects, produce qualitatively similar results. Hoxby and Avery (2012) and Black et al. (2015) use the conditional logit.

relies on variation of college characteristics within a student's score sending portfolio.[18] Since students send an average of seven score sends, there is substantial variation in the colleges to exploit.

3.2. Model 2 – Joint Applications

Student i has K colleges in her choice set and must choose the optimal portfolio of applications from among those colleges. Students must choose a portfolio of applications, P_{iT}, from the choice set, C_{iT} that maximizes utility, subject to the budget constraint in equation (4). Let the utility of a portfolio be written as:

$$U(P_{iT} \mid \Omega_{iT}) = U\left(P_{iT} \mid X_{iT}, Z_{iT}^{P}, \tau_{ik}^{P}\right) \qquad (8)$$

Where Z_{iT}^{P} and τ_{ik}^{P} are the college and timing characteristics of the portfolio. Then the maximization problem implied by Model 2 is for a student to choose:

$$P_{iT}^{*} \text{ such that } U\left(P_{iT}^{*} \mid \Omega_{iT}\right) \geq U(P_{iT} \mid \Omega_{iT}) \text{ for all possible } P_{iT} \subseteq C_{iT} \text{ and } \theta \cdot \overline{K} \leq \omega_i \qquad (9)$$

3.2.1. Estimation

To estimate the optimal portfolio, I simulate marginally different portfolios of applications that were *not* chosen. I use the actual and simulated portfolios to estimate the utility of certain characteristics of a portfolio with a revealed preference strategy- students get more utility from the observed portfolio than from the simulated portfolios that were not chosen.[19] I start by simulating portfolios of applications with the following algorithm:

1) Start with the observed application portfolio P_{iT}, which consists of $\overline{K}$ colleges.

2) Remove one of the observed applications from the application set P_{iT}.

[18] Another consequence of the fixed effects model is that there is no within student variation to exploit for the approximately 20 percent of students who send applications to all the colleges to which they send scores. These students typically send scores to very few colleges.
[19] A similar strategy of simulating portfolios is used in Arcidiacono (2005).

3) Take one score send from the choice set C_{iT} that did not become an application and add it to the portfolio from step 2 (that has one fewer application) to create a simulated portfolio $P_{iT}^{'}$ (with the same number of applications as P_{iT}).[20]

4) Calculate key statistics on the simulated portfolio $P_{iT}^{'}$, namely the average characteristics of the colleges in the portfolio (e.g., graduation rate or fraction in-state public flagships).

5) Repeat steps 3 and 4 for each observed application in the observed portfolio P_{iT} .

6) Repeat steps 2 through 5 for each score send in the choice set C_{iT} that did not become an application.

To illustrate the algorithm, Appendix Table 2 shows five hypothetical scenarios observed in the data. The first example shows a student who sent scores to College A, B, and C but only applied to College A. This example leads to two simulated portfolios, shown in the last column, whereby we replace College A with College B (the first simulated portfolio) and separately we replace College A with College C (the second simulated portfolio). This produced two new portfolios to compare to the original portfolio (just College A). The second example walks through a scenario with three score sends but two applications, which also produces two simulated portfolios. The next three examples consider a student with four score sends and one, two, and three applications, respectively.

There are several important things to note with this algorithm. First, I only simulate portfolios of the same size as the observed portfolio. This can be justified by assuming that the

[20] This requires that one such score send exists. I exclude the small number of students who converted all score sends into applications.

marginal utility from even the least preferred school far outweighs the marginal cost. This small assumption implies that the budget constraint is always as close to binding as integers will allow and that there is no such portfolio with fewer applications that is preferred to any portfolio with more applications. Second, these simulated portfolios are only marginal changes to the observed portfolio, not larger changes that substitute multiple applications with different score sends.

Finally, in step 4, I create key statistics about the simulated (and observed) portfolios that mimic the attributes of a single application, as the right panel of Table 2 demonstrates. Each observation is the (unweighted) average across colleges in the portfolio. Notice that these statistics mirror the left panel because the simulated portfolios are small perturbations from the observed portfolio. The big difference is that only 5.4 percent of the portfolios are applied to, which implies that each student is associated with approximately 20 portfolios (one observed and the rest simulated).

With the simulated and observed portfolio in hand and the maximization problem in equation (9), I once again can assume linearity in equation (8) such that it can be rewritten as follows:

$$U\left(P_{iT} \mid X_{iT}, Z_{iT}^{P}, \tau_{ik}^{P}\right) = \alpha^{P} + \beta^{P} Z_{iT}^{P} + \gamma^{P} X_{iT} + \varepsilon_{ik}^{P} \qquad (10)$$

Let $A_{ik}^{P} = 1$ if the student applies to college k in portfolio P and $A_{ik}^{P} = 0$ if not, such that I can estimate the probability of applying to an application portfolio using OLS with the following specification[21]:

$$P\left(A_{ik}^{P} = 1 \mid \Omega_{iT}\right) = \alpha^{P} + \beta^{P} Z_{iT}^{P} + \gamma^{P} X_{iT} + \varepsilon_{ik}^{P} \qquad (11)$$

[21] Conditional logit models require a different assumption on the error term, produce qualitatively similar results, and are shown in Appendix Table 5.

In practice, the main specification uses a student fixed effect, such that student invariant characteristics in X_{iT} are excluded. Again, with the fixed effect models, identification comes from variation of potential portfolios within a student's set of portfolios.

3.3. Timing

As of yet, the sequencing and timing of score sends has not played a role in the estimation. Students' preferences and college characteristics can change as time evolves but at the application deadline *T*, these weights and variables are set. This implies that colleges that enter the choice set in the early periods may eventually be valued differently at time *T* or more formally, $U(s_{ikt} \mid \Omega_{it}) \neq U(s_{ikT} \mid \Omega_{iT})$ and similarly $U(P_{it} \mid \Omega_{it}) \neq U(P_{iT} \mid \Omega_{iT})$.[22]

I formally test the idea that score sends (or portfolios) that are sent at different times have different probabilities of becoming applications. By doing so, I provide evidence that students preferences, information, and/or decision making changes as time evolves. To do so, I take a simplistic reduced-form approach and include measures of timing (τ_{ik}, which include a set of dummies for the month/season of score send and whether free) in the regressions. Specifically, for Model 1, I estimate:

$$P(A_{ik} = 1 \mid \Omega_{iT}) = \alpha + \beta z_{ikT} + \gamma X_{iT} + \tau_{ik} + \varepsilon_{ik} \qquad (12)$$

And for Model 2, I estimate:

$$P(A_{ik}^{P} = 1 \mid \Omega_{iT}) = \alpha^{P} + \beta^{P} Z_{iT}^{P} + \gamma^{P} X_{iT} + \tau_{ik}^{P} + \varepsilon_{ik}^{P} \qquad (13)$$

These specifications test whether the timing of score sends is related to the probability of application and therefore, students' application process is in part sequential. It is important to

[22] Note that we never observe P_{it}, only P_{iT}.

note that equations 12 and 13 are reduced-form estimates of the model and the timing variables (τ_{ik}) do not actually enter students' utility.

4. Results

4.1. Model 1 – Independent Applications

The primary results from Model 1 (independent applications) are in Table 3. The outcome is whether the student applies to the college and the first column uses OLS to estimate equation (7). The student characteristics (X_{iT}) are the same as those in Table 1: sex, ethnicity, student SAT score and number of attempts, and high school GPA. The college characteristics (z_{ikT}) are the same as in Table 2: average SAT, six-year graduation rate, instate tuition, distance from home (and its square), and mutually exclusive dummies for being an instate public flagship, instate public non-flagship, instate private, or out of state public (the omitted variable is out of state private).[23] Robust standard errors are used.

The coefficient on average SAT is not a good predictor of whether a student will apply but six-year graduation rates are positively related. A 10 percentage point increase in graduation rate translates into a 3 percentage point increase in the probability of applying conditional on sending a score to that college. Since average SAT scores are perhaps the most visible characteristic of a college, especially early in the decision making process, perhaps students only learn about graduation rates after a more thoughtful investigation into which colleges to apply, conditional on sending a score. Restated, students initially know average SAT scores but not graduation rates. Alternatively, the impact of average SAT on conversion may not be linear, especially given the qualitative and non-linear application advice around "safety," "match," and "reach"

[23] There are also dummies in the rare event that these variables are missing.

colleges, which we explore in Section 4.4. As expected, higher tuition and more distance translate into lower probabilities of applying to the college. The quadratic term on distance is positive implying some non-linearities but the relationship between the probability of applying and distance is strictly increasing at all possible values of distance. Relative to an out of state private college, out of state publics are 10.8 percentage points less likely to convert into applications. Approximately 45 percent of the students send scores to instate flagships, a popular choice for these HALIs, but given their high achievement, they are not more likely to apply to a flagship than out of state privates, where they may receive generous financial aid offerings. Alternatively, flagship status may not be appealing over and above graduation rates and average SATs. Also, larger colleges attract more applications.

The second column adds on the timing variable “free score send” and corresponds to equation (12). If the score send was free, which means it typically occurred earlier than many non-free score sends and prior to when students know their SAT score, there is an 11.76 percentage point lower probability of applying to that college. This is consistent with Bond et al. (2017) who find that students adjust their score sends in response to new information about their academic ability like receiving SAT scores. Column (3) shows the result of equation (10) that only includes the set of dummies for month/season of score sends. Relative to score sends sent after January of senior year, the earliest score sends are approximately 20 percentage points less likely to convert to applications. However, conditional on all the other college characteristics, there is no difference in the probability of application for score sends that are sent between the summer prior to one’s senior year and the latest of score sends after January of senior year.

Lastly, in column (4), I include both timing variables, which are correlated with one another. The coefficient on free score sends drops dramatically to -0.0378 but is still statistically different than zero. Even conditional on score sends being free, the earliest of score sends are still very unlikely to convert to applications compared to later score sends.

The next four columns are the preferred specification for Model 1 as it includes a student fixed effect. Therefore, identification comes from variation in the college characteristics and timing within a student's choice set. There are few qualitative differences relative to the previously described results that simply control for student characteristics. In fact, there are few quantitative differences with the previously described results as it relates to college characteristics, suggesting that student unobservables may not be correlated with the college characteristics of their score sends or perhaps the subset of HALIs have similar preferences. However, we do see some differences in the magnitude of the coefficients on the timing of score sends when including student fixed effects, which indicates that students do send scores at different times from one another.

4.2. Joint Applications

Table 4 is analogous to the Table 3 but include the estimates for Model 2 where students jointly choose their applications. For estimation, the unit of observation is a portfolio of colleges and so the variables included are the average characteristics of the portfolio, not individual institutions. The outcomes is whether the student applies to that portfolio, which occurs exactly once for each student.

In the first column of Model 2 results, which corresponds to equation (11), there are mostly similarities and few differences relative to Model 1 results. For example, similar to Model 1, there is no statistical association between average SAT of the portfolio of colleges and the probability of applying to the portfolio, however, unlike Model 1, there is no statistical relationship with graduation rates when using OLS. The positive relationship between graduation rates and score sends converting to applications reappears in the preferred specification with student fixed effects (column 5). Also, if the average tuition of a portfolio increases by $1,000, students are 0.34 percent less likely to apply to that portfolio, all else equal. As in the previous model, there is also a strong negative relationship between distance from home and application conversion. Portfolios with public flagships are more likely to receive applications, though, this is not robust to including student fixed effects. Portfolios with relatively more out of state public colleges are not likely to be chosen, just as in Model 1.

Keep in mind, the variables in this model use the *average* of the entire portfolio, not a single application. Most portfolios have about four applications and so one can think about how students value individual colleges. For example, increasing the average number of out of state public colleges in the portfolio by say 25 percentage points occurs if an average sized portfolio has one additional out of state public college. The coefficient of -0.09 implies that adding the additional college to the portfolio and increasing the average number of out of state publics by 25 percentage points translates to a 2.25 percentage point decrease (-0.09*25) in choosing that portfolio.

In column (6), I introduce the timing variable "free score send" such that the specification corresponds to equation (13). Portfolios that consist of more free score sends are less likely to be chosen. At the extreme, a portfolio with all free score sends compared to one with no free score sends would be 26 percent less likely to be chosen, all else equal. Column (7) includes the set of month/season variables. In the portfolio model, these are not actually dummies but measures of the percent of score sends with the underlying dummies and hence are not mutually exclusive. The coefficients get increasingly large as time goes on, which is consistent with the previous results that early score sends (and portfolios with early score sends) are unlikely to convert to applications (or be chosen). The last column of the table includes all the timing variables and as before, the coefficient on free score sends drops in magnitude (and out of statistical significance) but there are clear differences in the coefficients on early score sends versus late score sends that are statistically different from one another (even if not different from zero).

4.3. Robustness Tests

I perform several robustness tests on each model's preferred specification from Tables 3 and 4, which include student fixed effects and all measures of timing. The results of these tests are in Table 5.

The first concern is that students may apply to college with early admission or action and therefore only ever send one application without thinking of the portfolio. I re-run the analyses only including students who had more than one application. Estimates (columns 1 and 6) are largely unchanged in part because most of these students, perhaps unsurprisingly, did not receive offers of admission through early decision or early action plans.[24]

A second concern is that students also take the ACT and choose to send these ACT scores but not their SAT scores. This would mean that we observe a truncated choice set. I re-run the analyses on the subset of students who sent at least one score send after their last SAT is taken. This is a deliberate and costly action that is most likely to occur if the student is using her SAT score in the application process. Again, results are largely unchanged in both models (columns 2 and 7) primarily because this subset includes most SAT-takers.

[24] Early action and early decision enrollment skews heavily toward wealthy students.

Third, although the survey of students only asks for information on 10 applications, a question about the total number of college applications permits me to re-run the analyses on the subset of SAT-takers who applied to fewer than 10 colleges. The results are largely unchanged (columns 3 and 8).

Fourth, low-income students who register for the SAT with a fee waiver also have the option to get four more "flexible" score sends. These score sends are free and can be sent at any time, unlike the "free upon registration" score sends. I replicate my analyses on the subset of students who did not register for the SAT with a fee waiver in order to omit students who may have used free non-registration fee-waivers. Results are largely unchanged (columns 4 and 9).

Finally, I weight the sample to reflect the racial composition of HALIs since the survey oversampled racial minorities. Results are in columns (5) and (10) and are largely unchanged.

Combined, Table 5 shows that the results are robust to a number of potential issues. Specifically, graduation rates and enrollment size are consistently positive and tuition, distance from home, and out of state publics are almost always negative and statistically significant. As for timing, free score sends always have negative relationship with applications and are always statistically significant in Model 1 specifications and sometime in Model 2 specifications.

I perform several more robustness tests that are in the appendix. First, I change the timing variable from a set of month/season dummies to months relative to the mean in the sample. I use specifications with just the linear term and separately including the quadratic term. As Appendix Table 3 shows, in all models there is a positive coefficient on date, confirming that score sends sent later in time are more likely to convert to applications, even conditional on whether it is a free score send. The quadratic term is not statistically different than zero.

Next, Appendix Table 4 deals explicitly with students who had applications with no corresponding score send. Those students' observed score sends are included in the primary analysis but the non-existent score sends are clearly not. I re-run the Model 1 preferred specification with fixed effects but only include students for which there are certain numbers of missing score sends. I start by including only the students who are missing fewer than six score sends given their stated applications. I progressively go from missing fewer than five score sends on until I only include students who are not missing any score sends. As Appendix Table 4 shows, in specifications that use the fewest students (only those with almost no missing score sends), statistical power is an issue, but overall, the qualitative results are unchanged.

Finally, I also estimate Model 2 using a conditional logit and results are qualitatively similar.[25] The logit estimates are in the first column of Appendix Table 5.[26]

4.4. Additional Portfolio Attributes

Whether score sends convert into applications are not entirely determined by college characteristics but also how they intersect with student characteristics and the characteristics of other score sends. Table 6 explores some alternative explanatory variables that address this issue.

In columns (1) and (4), corresponding to Models 1 and 2, respectively, the average SAT of the college is replaced by the difference between the students' SAT and the average SAT of the college. This is a measure often referred to as "match," which quantifies how similar a student's academic ability is to the colleges', as measured by SAT. Students may be counseled to consider

[25] A student can choose to apply to more than one college in the consideration set so the conditional logit is inappropriate for Model 1.
[26] The coefficients are presented as odds ratio, so a coefficient larger than one is an increase in the probability of a score send converting to an application and a coefficient less than one is a decrease.

match in the application process. However, we do not see any statistical relationship between this measure of match and application conversion. This may be because the assumption of linearity is too strong and so columns (2) and (5) use the concept of "safety" and "reach" colleges. While there are negative coefficients on safety colleges, they are not statistically significant. On the other hand, the coefficients on reach colleges are negative and statistically significant. This suggests that students are less likely to apply to colleges that are less likely to accept them than the omitted match colleges. This is consistent with results in column (3) whereby students are more likely to apply to colleges with higher average SAT but the quadratic term suggests this is less true at high SAT level (i.e., reaches). Though, the results in column (6) do not suggest this relationship.

Finally, using Model 2, I assess how students value the portfolio as a whole, including the range of colleges in the portfolio. Column (7) shows that portfolios where the minimum average SAT is higher are more likely to be chosen than when it is lower and portfolios where the maximum average SAT is lower are more likely to be chosen than when it is higher. This suggests that students do not have strong preferences for extremely disparate applications and rather, they prefer colleges that are somewhat similar to each other- not too much of a safety and not too much of a reach.

Overall, the preponderance of evidence from Table 6 suggests that students prefer score sends and portfolios that are not far from their own measured ability. This might relate to the advice they receive from parents or counselors and may also relate to their level or risk tolerance.

4.5. Heterogeneous Effects

Testing for heterogeneous effects is limited by the sample size. I divide the sample and conduct two analyses: male versus female and underrepresented minority (black or Hispanic) versus not (white and Asian). There are very few differences by these subgroups, in part due to statistical power, and so I only present results in Appendix Table 6.[27] Perhaps the only thing of note is that males are less likely to apply to portfolios with flagships and out of state public colleges than females. The lack of differences between underrepresented minority students and non-underrepresented minorities is surprising at first glance. However, these students are very high achieving and underrepresented minorities at the highest end of the measured academic ability spectrum have different application patterns than those elsewhere in the distribution. This is in part because those students have great opportunities and tend to be sought after by colleges who value diversity and in addition, there are many organizations that aim to improve the college application and enrollment experience for these students (e.g., Hoxby and Turner, 2013 and outreach by the College Board).

4.6. Enrollment

Next, I consider the relationship between the characteristics of score sends (and applications) and eventual enrollment. This is not necessarily the same as the relationship between score sends and applications. I also consider the relationship between application and enrollment.

This analysis is similar in spirit to Long (2004), who looks at the determinants of where students enroll among the entire set of colleges in the U.S. She is particularly interested in the dynamics of average SAT scores, tuition, and distance from home as she shows their relative

[27] The results are for Model 2 but Model 1 yields qualitatively similar results.

importance over several decades. This analysis differs in two ways. First, I take one step back, by looking at score send conversion to enrollment, along with applications to enrollment, which means I only consider the determinants of enrollment from a refined choice set. Second, I am able to see how the timing of score sends relates to enrollment, which has never been examined.

Similar to Long (2004), one should expect a student's score sends to convert to enrollment when there is low tuition, high SAT scores, and closer to home. Though, none of these are necessary if students underestimate or overestimate their probabilities of acceptance. As for timing variables, there are two primary but disparate scenarios worth noting. First, score sends may be relatively uniformed decisions throughout the application process and so when the time comes to enroll, there is no relationship between timing of score sends and enrollment. Second, the timing of score sends may say a lot about student preferences for a college. On the early side, students always planned to attend College X if admitted and so sending their SAT scores early in the process was never a question. On the late side, students may scramble to meet a deadline or find a college late in the application process that is an exceptionally good fit. Thus, the timing of score sends would be a good indicator of how likely a student is to enroll but the direction is an empirical question. The above examples are not the only potential scenarios that could dictate the relationship between score send timing and enrollment but based on previous literature, students tend not to overthink the application process and therefore, these are the leading candidates driving the empirics.

I estimate the factors associated with a score send and college application converting into students' enrollment choice using a strategy similar to Model 1 (equation 6). However, there need not be any assumptions on whether students choose applications independently or jointly, since there is at most one choice of enrollment. Results based on OLS with student fixed effects are presented in Table 7. The first column estimates how score sends relate to enrollment. The second column estimates how applications relate to enrollment. Unlike the previous analyses, it is important to account for the role of the admission process in enrollment through controls for measures of selectivity (e.g., average SATs and graduation rate).[28]

Similar to the application analyses (Tables 3 and 4), there is no statistical relationship between average SAT score and the probability of enrollment in the first column of Table 7. Unlike the results from the application analyses, there is a slightly negative coefficient on six-year graduation rate. Taken together, these results imply that score sends are more likely to convert to high graduation rate college applications but less likely to convert to high graduation rate college choice. All else equal, average SAT is not a big determinant in application or enrollment. Again, the relative importance of average SAT and graduation rates may have to do with students' prior knowledge of the statistics. The probability of enrollment is negatively (and non-linearly) related to distance from home, as it was with the probability of application. The two columns of results have coefficients that are similar in magnitude to one another, suggesting that much of the negative enrollment effect is driven by students not applying to the college, which is consistent with recent research in the area (Smith et al., 2013; Hoxby and Turner, 2013). The sign of the coefficients on out of state public colleges is the same as the sign of the coefficient in the application regression. However, instate public flagship is extremely positive, despite not being robustly related to the probability of an application. It is difficult to pin down what drives these differences. Is it that students learn more about flagships after they've applied? Or flagships give better (and unexpected) financial aid? Or perhaps instate students

[28] In results not, shown, controlling for acceptance rate adds little to the model. The coefficient estimate on acceptance rate is zero and all other coefficients are unchanged.

have a much higher probability of acceptance at flagships than their applications to selective private colleges.

Moving to the bottom of the first column, the coefficient on free score sends is positive and marginally significant. This is in stark contrast to the negative coefficients in the application stage. Similarly, the coefficients on the latest applications well into one's senior year are negative- the opposite sign as the application stage.

The last column finds some results consistent with Long (2004). In particular, conditional on applying, students are more likely to enroll in colleges with higher average SATs. I do not find that distance is a great predictor, but again, these results are conditional on factors such as whether the college is in-state. Students are much less likely to enroll in out of state publics, conditional on an application. Finally, a free score send that turns into an application is 4.8 percentage points more likely to lead to enrollment than one that was not free and again, we see negative coefficients on late score sends (not statistically significant). These are in stark contrast to the relationships on the probability of applying.

Overall, the results of Table 7 tell two stories. First, the same college characteristics that influence conversion to applications often, but not always, influence the conversion to enrollment. Second, the timing variables that relate to application conversion work in the opposite direction as the way they relate to enrollment conversion. Specifically, score sends that are chosen relatively early do not often end in application but if they do, they tend to end up in enrollment. What can explain this pattern? One explanation consistent with the data is that free score sends go to a range of colleges known by students, those that are highly preferable (that end in enrollment) and those that are not well thought out (that don't get an application). This is not surprising given since students in the early stages of building a portfolio are likely to start with what they know (e.g., local colleges, colleges in the news, colleges their friends or teacher went to). As time passes and students learn about their abilities, options, and those colleges, they may remove some from their choice set but one or two of them remain and end in enrollment.

5. Conclusion

The results of this paper are clear- students' application portfolios change over time. Some applications are decided upon early and others are decided much later but they are certainly not chosen at the same time. This may not be surprising to those outside the research community, especially counselors and parents. The simplifying assumptions that most education researchers make are understandable, given their data constraints. Most researchers only observe the final application portfolio, not how it was constructed. However, doing so implies that the simultaneous choice models, which are often used, lose valuable information on what applications are being impacted. Again, back to the simple example, if a student decides early on to apply to a college, the optimization problem down the road is how to construct a portfolio that already has one college in it. There should be more thought and discussion into how data and model limitations differ from reality and how the assumptions used to overcome the issues may impact the information obtained and potentially the estimates.

From a policy perspective, these results shed light on several topical issues. There is a lot of effort to provide students with information to make good choices. This ranges from no-touch websites (e.g. College Scorecard, College Navigator, U.S. News, and World Report, and Big Future), to low-touch interventions (e.g. Hoxby and Turner, 2013), to high-touch counseling (e.g. Carrell and Sacerdote, 2015). But which colleges in the students' choice set are these interventions impacting? Is it the ones chosen early that students have strong (or weak) preferences for? Is it the ones that come late to round out their portfolio once more information is aggregated? More importantly, does this mean the impact of an intervention depends on the timing in part because students' early choices are more or less malleable? These answers are especially important if the aforementioned colleges differ in quality or fit. In addition, the results suggest that preferences evolve over time and so perhaps frequent discussions, interventions, or counseling sessions are important. This would likely require research, funding, and the support of institutions.

This paper is also relevant to colleges, admissions officers, and enrollment managers. A lot of time and money is spent trying to identify and recruit prospective students to become applicants and eventually matriculants. They could harness this information about the timing of student contact to evaluate whether they should invest more energy in the student or divert their resources elsewhere. Similarly, colleges have applicants of varying backgrounds and so the results of this paper may differ depending on the target population. Colleges could use their own data to further investigate score sending patterns and conversion to applications may prove informative. Related, there may be information in the timing of applications that colleges can harness.

This research also sets the stage for future research. First, there is a need for interventions at different times in a student's decision process to see how applications differentially shift, if at all. Second, this paper was also performed on a non-representative sample and it would be worthwhile to run similar analyses on a more diverse pool of students. Lower-achieving students tend to send fewer score sends (and applications) than higher-achieving students, so the results of this paper may be less applicable. However, higher-income students that are comparably high-achieving tend to send the most score sends (and applications) and therefore, likely have some parallels of non-conversion. Third, this paper makes no effort to understand how the colleges get into a students' choice set and whether the conversion to applications are demand driven (e.g., early decision) or supply driven (e.g., student preferences). Is it more efficient (or possible) to change the choice set or the low-hanging fruit of converting score sends into applications? Finally, this paper merely describes the sequential nature of college applications and future theoretical and econometric models should be enhanced to account for this fact.

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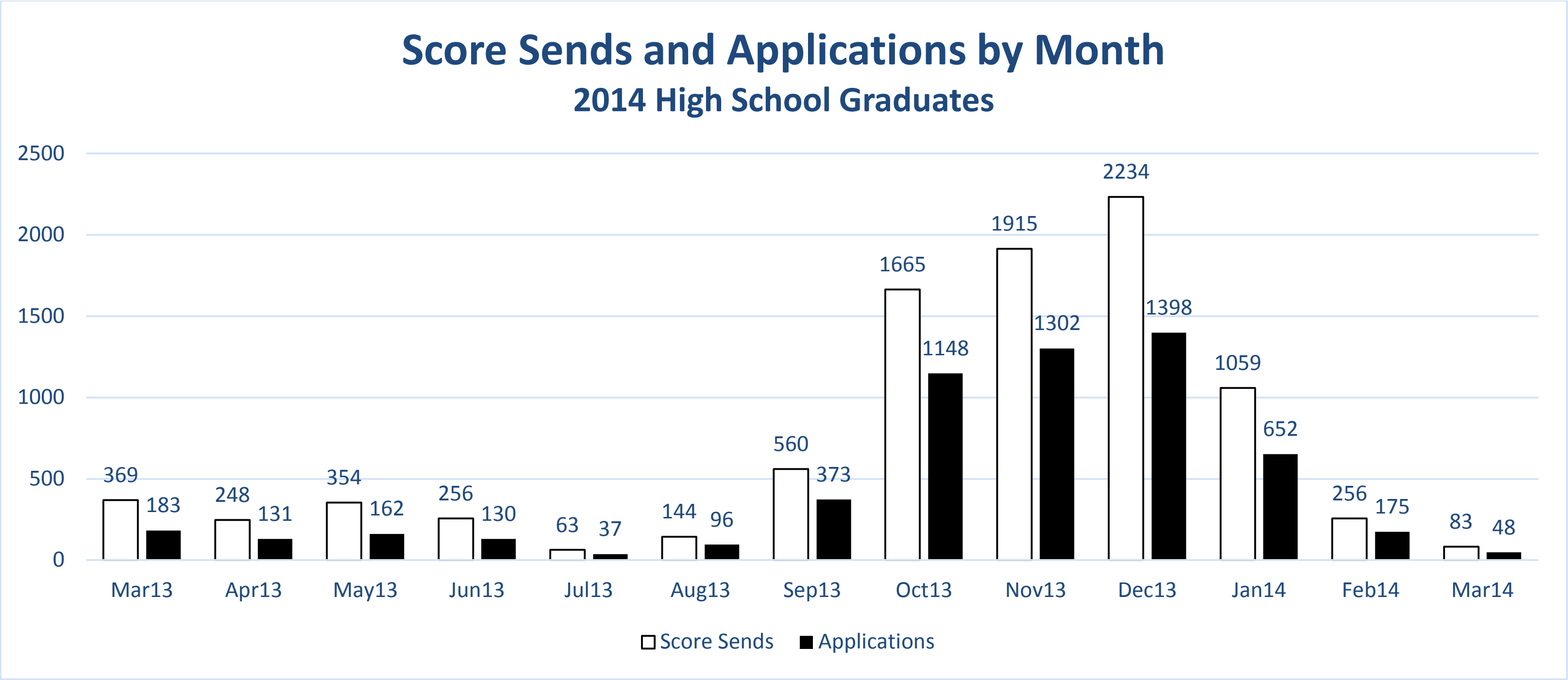
Figure 1



Notes: Sample includes high-achieving low-income students who responded to a College Board survey about the application process and sent at least one SAT score send and application to a four-year college. Score sends are sent in the above months but applications associated with those score sends can be sent at any time.

Table 1: Student Summary Statistics

Variable	*Mean*	*Std. Dev.*	*Min*	*Max*
Male	0.518	0.500	0	1
White	0.232	0.423	0	1
Black	0.205	0.404	0	1
Hispanic	0.266	0.442	0	1
Asian	0.269	0.443	0	1
Other Race	0.027	0.162	0	1
Northeast	0.248	0.432	0	1
Midwest	0.087	0.282	0	1
South	0.325	0.469	0	1
West	0.335	0.472	0	1
High School GPA	3.892	0.397	1.670	4.330
SAT Score	1329	93	830	1600
SAT Attempts	1.987	0.822	1	9
Number of Score Sends	6.994	4.646	1	27
Number of Applications	4.353	3.099	1	20
Average SAT of Score Sends (100s)	1278	109	925	1508
Average Distance of Score Sends (100s of Miles)	5.666	5.322	0.006127	29.7044
N = 1,441				

Notes: Sample includes high-achieving low-income students who responded to a College Board survey about the application process and sent at least one SAT Score Send and application to a four-year college.

Table 2: Score Send and Application Portfolio Summary Statistics

	Obs = Score Send (N = 10,073)				*Obs = Simulated and Actual Application Portfolio (N = 20,503)*			
Variable	*Mean*	*Std. Dev.*	*Min*	*Max*	*Mean*	*Std. Dev.*	*Min*	*Max*
Student Action								
Applied	0.623	0.485	0	1	0.054	0.225	0	1
Enrolled	0.122	0.327	0	1	--	--	--	--
College Attributes								
Average SAT (100s)	13.020	1.460	8.250	15.250	13.186	0.958	9.125	15.250
Safety	0.312	0.463	0	1	0.293	0.271	0	1
Match	0.506	0.500	0	1	0.526	0.259	0	1
Reach	0.183	0.387	0	1	0.181	0.246	0	1
Six-Year Graduation Rate	80.975	14.978	12.000	100.000	82.596	9.503	26.000	97.000
Tuition and Fees ($1,000s)	31.673	14.241	0.000	49.793	33.340	8.331	0.000	47.246
Distance from Home (100s of miles)	6.682	7.918	0.001	33.389	7.264	5.271	0.011	31.915
Instate Public Flagship	0.067	0.250	0	1	0.057	0.097	0	1
Instate Public Non-Flagship	0.176	0.381	0	1	0.147	0.212	0	1
Instate Private	0.150	0.357	0	1	0.141	0.185	0	1
Out of State Public	0.135	0.341	0	1	0.135	0.182	0	1
Out of State Private	0.472	0.499	0	1	0.520	0.291	0	1
First-time Full-time Enrollment (1,000s)	2.582	1.896	0.000	8.393	2.506	1.024	0.096	8.393
Score Send Attributes								
Free Score Send	0.334	0.472	0	1	0.327	0.363	0	1
Sent Prior to Spring Junior Year (Apr 2013)	0.117	0.321	0	1	0.123	0.244	0	1
Sent Spring Junior Year (Apr-Jun 2013)	0.085	0.279	0	1	0.078	0.202	0	1
Sent Summer Prior to Senior Year (Jul-Aug 2	0.021	0.142	0	1	0.017	0.097	0	1
Sent Fall Senior Year (Sept-Nov 2013)	0.411	0.492	0	1	0.403	0.346	0	1
Sent Winter Senior Year (Dec 2013-Jan 201	0.327	0.469	0	1	0.345	0.341	0	1
Sent Late Senior Year (After Jan 2014)	0.040	0.195	0	1	0.027	0.105	0	1

Notes: In the left panel, an observation is a student score send for high-achieving low-income students who respond to a College Board survey and sent at least one score send and application. In the right panel, an observation is the average of the applications characteristics in a simulated portfolio. A simulated portfolio consists of the same number of observed applications but removes one application and substitutes with a student's score send that was not an application. This is done for all possible applications being substituted with all possible Score sends that were not applications. Simulated portfolios require at least one score send that was not an application.

Table 3: Score Sends to Application Conversion - Model 1 (Independent Applications)

	OLS				Student FE			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
College Attributes								
Average SAT (100s)	-0.0122	-0.0073	-0.0061	-0.0053	-0.0076	-0.0052	-0.0064	-0.0057
	(0.0076)	(0.0076)	(0.0076)	(0.0076)	(0.0089)	(0.0088)	(0.0088)	(0.0087)
Six-Year Graduation Rate	0.0030***	0.0029***	0.0028***	0.0027***	0.0028***	0.0029***	0.0030***	0.0030***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Tuition and Fees ($1,000s)	-0.0029**	-0.0037***	-0.0040***	-0.0040***	-0.0026*	-0.0028*	-0.0030**	-0.0030**
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0014)	(0.0014)	(0.0014)	(0.0014)
Distance from Home (100s of miles)	-0.0113***	-0.0105***	-0.0119***	-0.0116***	-0.0090**	-0.0096***	-0.0103***	-0.0102***
	(0.0028)	(0.0028)	(0.0028)	(0.0028)	(0.0037)	(0.0037)	(0.0036)	(0.0036)
Distance from Home Squared	0.0026**	0.0023**	0.0028***	0.0027***	0.0021	0.0023*	0.0026*	0.0026*
	(0.0011)	(0.0011)	(0.0010)	(0.0010)	(0.0014)	(0.0013)	(0.0013)	(0.0013)
Instate Public Flagship	0.0206	0.0148	0.0060	0.0059	0.0397	0.0412	0.0364	0.0364
	(0.0441)	(0.0438)	(0.0437)	(0.0437)	(0.0523)	(0.0523)	(0.0521)	(0.0522)
Instate Public Non-Flagship	-0.0082	-0.0205	-0.0306	-0.0313	0.0327	0.0309	0.0260	0.0259
	(0.0391)	(0.0388)	(0.0387)	(0.0387)	(0.0474)	(0.0474)	(0.0471)	(0.0472)
Instate Private	0.0234	0.0313*	0.0303*	0.0311*	0.0500**	0.0534***	0.0544***	0.0549***
	(0.0173)	(0.0173)	(0.0172)	(0.0172)	(0.0199)	(0.0198)	(0.0198)	(0.0198)
Out of State Public	-0.1084***	-0.1136***	-0.1171***	-0.1179***	-0.1225***	-0.1226***	-0.1289***	-0.1292***
	(0.0235)	(0.0234)	(0.0232)	(0.0232)	(0.0271)	(0.0271)	(0.0268)	(0.0269)
First-time Full-time Enrollment (1,000s)	0.0145***	0.0148***	0.0153***	0.0150***	0.0172***	0.0177***	0.0177***	0.0176***
	(0.0035)	(0.0035)	(0.0035)	(0.0035)	(0.0041)	(0.0041)	(0.0041)	(0.0041)
Score Send Attributes								
Free Score Send	--	-0.1176***	--	-0.0378***	--	-0.1111***	--	-0.0584**
	--	(0.0103)	--	(0.0137)	--	(0.0192)	--	(0.0234)
Sent Prior to Spring Junior Year (Apr 2013)	--	--	-0.2005***	-0.1653***	--	--	-0.1309***	-0.0791*
	--	--	(0.0276)	(0.0304)	--	--	(0.0394)	(0.0447)
Sent Spring Junior Year (Apr-Jun 2013)	--	--	-0.1958***	-0.1620***	--	--	-0.1219***	-0.0747
	--	--	(0.0289)	(0.0314)	--	--	(0.0429)	(0.0465)
Sent Summer Prior to Senior Year (Jul-Aug 201	--	--	-0.0472	-0.0343	--	--	-0.0002	0.0202
	--	--	(0.0397)	(0.0400)	--	--	(0.0546)	(0.0551)
Sent Fall Senior Year (Sept-Nov 2013)	--	--	0.0024	0.0125	--	--	0.0598*	0.0762**
	--	--	(0.0247)	(0.0249)	--	--	(0.0338)	(0.0343)
Sent Winter Senior Year (Dec 2013-Jan 2014)	--	--	-0.0298	-0.0281	--	--	0.0159	0.0197
	--	--	(0.0252)	(0.0252)	--	--	(0.0347)	(0.0346)
Student Characteristic Controls	Yes	Yes	Yes	Yes	No	No	No	No
Observations	10,073	10,073	10,073	10,073	10,073	10,073	10,073	10,073
R-squared	0.037	0.049	0.060	0.061	0.034	0.040	0.045	0.046

Notes: The unit of observation is a score send. Standard errors are presented in parentheses and statistical significance is reported as follows: *** p<0.01, ** p<0.05, * p<0.1. Student characteristic controls include sex and ethnicity dummies, student SAT and number of SAT attempts, and high school GPA. Additional controls in all regressions include dummies for missing values or college average SAT, graduation rate, tuition and fees, and distance from home. Score sends are observed in administrative data and applications come from survey data.

Table 4: Score Sends to Application Conversion - Model 2 (Joint Applications)

	OLS				Student FE			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
College Attributes								
Average SAT (100s)	0.0016	0.0016	0.0026	0.0018	-0.0345*	-0.0272	-0.0263	-0.0256
	(0.0067)	(0.0067)	(0.0068)	(0.0068)	(0.0188)	(0.0189)	(0.0189)	(0.0189)
Six-Year Graduation Rate	0.0004	0.0004	0.0005	0.0005	0.0046**	0.0048***	0.0050***	0.0050***
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0018)	(0.0018)	(0.0018)	(0.0018)
Tuition and Fees ($1,000s)	-0.0034***	-0.0034***	-0.0037***	-0.0037***	-0.0040	-0.0042	-0.0048	-0.0048
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0031)	(0.0031)	(0.0031)	(0.0031)
Distance from Home (100s of miles)	-0.0050***	-0.0050***	-0.0052***	-0.0055***	-0.0193**	-0.0210***	-0.0259***	-0.0255***
	(0.0014)	(0.0014)	(0.0014)	(0.0015)	(0.0081)	(0.0079)	(0.0080)	(0.0080)
Distance from Home Squared	0.0001***	0.0001***	0.0002***	0.0002***	0.0006**	0.0006**	0.0008***	0.0008***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Instate Public Flagship	0.1315**	0.1316**	0.1266**	0.1251**	0.1097	0.1026	0.0953	0.0949
	(0.0511)	(0.0511)	(0.0516)	(0.0516)	(0.1166)	(0.1184)	(0.1190)	(0.1192)
Instate Public Non-Flagship	-0.0426	-0.0428	-0.0509	-0.0501	0.0438	0.0323	0.0165	0.0167
	(0.0373)	(0.0374)	(0.0376)	(0.0377)	(0.1012)	(0.1024)	(0.1036)	(0.1036)
Instate Private	0.0100	0.0101	0.0127	0.0116	0.0455	0.0492	0.0373	0.0389
	(0.0143)	(0.0143)	(0.0144)	(0.0144)	(0.0458)	(0.0452)	(0.0444)	(0.0444)
Out of State Public	-0.0904***	-0.0904***	-0.0931***	-0.0930***	-0.2615***	-0.2682***	-0.2736***	-0.2748***
	(0.0215)	(0.0215)	(0.0217)	(0.0217)	(0.0572)	(0.0587)	(0.0593)	(0.0594)
First-time Full-time Enrollment (1,000s)	0.0121***	0.0120***	0.0123***	0.0127***	0.0273***	0.0294***	0.0315***	0.0314***
	(0.0037)	(0.0038)	(0.0038)	(0.0038)	(0.0098)	(0.0099)	(0.0100)	(0.0100)
Score Send Attributes								
Free Score Send	--	-0.0007	--	0.0153*	--	-0.2587***	--	-0.0600
	--	(0.0054)	--	(0.0078)	--	(0.0363)	--	(0.0453)
Sent Prior to Spring Junior Year (Apr 2013)	--	--	0.0180	0.0153	--	--	-0.0215	-0.0197
	--	--	(0.0231)	(0.0232)	--	--	(0.1846)	(0.1855)
Sent Spring Junior Year (Apr-Jun 2013)	--	--	0.0323	0.0292	--	--	-0.0051	-0.0104
	--	--	(0.0251)	(0.0253)	--	--	(0.1883)	(0.1893)
Sent Summer Prior to Senior Year (Jul-Aug 201	--	--	0.0408	0.0475	--	--	0.2572	0.2209
	--	--	(0.0305)	(0.0306)	--	--	(0.2216)	(0.2260)
Sent Fall Senior Year (Sept-Nov 2013)	--	--	0.0389*	0.0468**	--	--	0.3425*	0.3080
	--	--	(0.0222)	(0.0225)	--	--	(0.1855)	(0.1893)
Sent Winter Senior Year (Dec 2013-Jan 2014)	--	--	0.0336	0.0446*	--	--	0.3875**	0.3384*
	--	--	(0.0227)	(0.0232)	--	--	(0.1856)	(0.1914)
Sent Late Senior Year (After Jan 2014)	--	--	0.1081***	0.1188***	--	--	0.4277**	0.3758*
	--	--	(0.0313)	(0.0316)	--	--	(0.2042)	(0.2112)
Student Characteristic Controls	Yes	Yes	Yes	Yes	No	No	No	No
Observations	20,503	20,503	20,503	20,503	20,503	20,503	20,503	20,503
R-squared	0.040	0.040	0.041	0.041	0.033	0.041	0.048	0.048

Notes: The unit of observation is a simulated application portolio, which have same number of applications of actual portfolio but substitutes observed score sends that did not become an application. Standard errors are presented in parentheses and statistical significance is reported as follows: *** p<0.01, ** p<0.05, * p<0.1. Student characteristic controls include sex and ethnicity dummies, student SAT and number of SAT attempts, and high school GPA. Additional controls in all regressions include dummies for missing values or college average SAT, graduation rate, tuition and fees, and distance from home. Score sends are observed in administrative data and applications come from survey data.

Table 5: Score Sends to Application Conversion - Robustness Tests

	Model 1: Score Sends					Model 2: Simulated Application Portfolios				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(8)	(10)
	At least 2 applications	Has Score Send after last SAT	Fewer than 10 applications on survey	No SAT fee waiver	Using sample weights	At least 2 applications	Has Score Send after last SAT	Fewer than 10 applications on survey	No SAT fee waiver	Using sample weights
College Attributes										
Average SAT (100s)	-0.0043	-0.0108	-0.0152	-0.0114	0.0038	-0.0301	-0.0416**	-0.0323	-0.0365*	-0.0161
	(0.0091)	(0.0092)	(0.0098)	(0.0093)	(0.0107)	(0.0236)	(0.0191)	(0.0208)	(0.0209)	(0.0238)
Six-Year Graduation Rate	0.0029***	0.0035***	0.0027***	0.0035***	0.0025**	0.0053**	0.0062***	0.0048**	0.0054***	0.0047**
	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0010)	(0.0023)	(0.0020)	(0.0020)	(0.0020)	(0.0023)
Tuition and Fees ($1,000s)	-0.0030**	-0.0033**	-0.0025	-0.0033**	-0.0036**	-0.0053	-0.0047	-0.0044	-0.0069**	-0.0038
	(0.0015)	(0.0015)	(0.0016)	(0.0016)	(0.0016)	(0.0037)	(0.0033)	(0.0033)	(0.0035)	(0.0036)
Distance from Home (100s of miles)	-0.0084**	-0.0075**	-0.0080*	-0.0083**	-0.0091**	-0.0121	-0.0167*	-0.0255***	-0.0237***	-0.0174*
	(0.0038)	(0.0038)	(0.0041)	(0.0039)	(0.0042)	(0.0096)	(0.0085)	(0.0089)	(0.0088)	(0.0093)
Distance from Home Squared	0.0020	0.0016	0.0018	0.0021	0.0022	0.0003	0.0005	0.0008***	0.0008**	0.0005*
	(0.0014)	(0.0014)	(0.0015)	(0.0015)	(0.0016)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Instate Public Flagship	0.0301	0.0200	0.0603	0.0133	0.0200	0.1136	0.1415	0.1191	-0.0043	0.1013
	(0.0536)	(0.0543)	(0.0563)	(0.0579)	(0.0592)	(0.1281)	(0.1275)	(0.1286)	(0.1372)	(0.1278)
Instate Public Non-Flagship	0.0267	0.0018	0.0315	0.0171	-0.0077	0.0456	-0.0192	0.0298	-0.0609	0.0099
	(0.0488)	(0.0494)	(0.0513)	(0.0530)	(0.0528)	(0.1171)	(0.1104)	(0.1123)	(0.1170)	(0.1126)
Instate Private	0.0572***	0.0548***	0.0428*	0.0584***	0.0573**	0.0834	0.0513	0.0311	0.0480	0.0461
	(0.0203)	(0.0205)	(0.0225)	(0.0212)	(0.0224)	(0.0519)	(0.0467)	(0.0498)	(0.0496)	(0.0510)
Out of State Public	-0.1255***	-0.1322***	-0.1406***	-0.1422***	-0.1232***	-0.3416***	-0.2817***	-0.2879***	-0.3419***	-0.2638***
	(0.0279)	(0.0277)	(0.0295)	(0.0295)	(0.0304)	(0.0703)	(0.0621)	(0.0652)	(0.0656)	(0.0670)
First-time Full-time Enrollment (1,000s)	0.0175***	0.0174***	0.0153***	0.0166***	0.0199***	0.0419***	0.0306***	0.0310***	0.0340***	0.0400***
	(0.0042)	(0.0042)	(0.0046)	(0.0044)	(0.0047)	(0.0109)	(0.0107)	(0.0110)	(0.0110)	(0.0113)
Score Send Attributes										
Free Score Send	-0.0594**	-0.0621***	-0.0737***	-0.0607**	-0.0590**	-0.0752*	-0.0323	-0.0621	-0.0738	-0.0555
	(0.0238)	(0.0239)	(0.0264)	(0.0272)	(0.0266)	(0.0450)	(0.0479)	(0.0519)	(0.0572)	(0.0484)
Sent Prior to Spring Junior Year (Apr 2013)	-0.0888*	-0.0848*	-0.1012**	-0.0894*	-0.0848*	0.1282	0.0014	-0.0438	-0.0104	-0.0092
	(0.0454)	(0.0460)	(0.0513)	(0.0523)	(0.0502)	(0.2720)	(0.1598)	(0.1966)	(0.1924)	(0.1698)
Sent Spring Junior Year (Apr-Jun 2013)	-0.0794*	-0.0786	-0.1148**	-0.1102**	-0.0271	0.1936	-0.0566	-0.0531	-0.0349	0.0567
	(0.0472)	(0.0482)	(0.0515)	(0.0552)	(0.0532)	(0.2716)	(0.1591)	(0.2013)	(0.1984)	(0.1753)
Sent Summer Prior to Senior Year (Jul-Aug 2013)	0.0114	0.0158	0.0427	0.0103	0.0103	0.3666	0.2491	0.2424	0.2188	0.2499
	(0.0546)	(0.0573)	(0.0619)	(0.0608)	(0.0671)	(0.2845)	(0.1988)	(0.2412)	(0.2412)	(0.2243)
Sent Fall Senior Year (Sept-Nov 2013)	0.0690**	0.0770**	0.0418	0.0601	0.0788**	0.5397**	0.3325**	0.2818	0.3042	0.3104*
	(0.0346)	(0.0344)	(0.0400)	(0.0390)	(0.0396)	(0.2733)	(0.1596)	(0.2019)	(0.1984)	(0.1731)
Sent Winter Senior Year (Dec 2013-Jan 2014)	0.0128	0.0178	0.0036	-0.0019	0.0480	0.6113**	0.3623**	0.2997	0.3177	0.3663**
	(0.0350)	(0.0347)	(0.0399)	(0.0394)	(0.0409)	(0.2740)	(0.1620)	(0.2051)	(0.2013)	(0.1764)
Sent Late Senior Year (After Jan 2014)	--	--	--	--	-	0.7704***	0.4146**	0.3450	0.4733**	0.3713*
	--	--	--	--		(0.2817)	(0.1826)	(0.2294)	(0.2218)	(0.2048)
Observations	9,377	9,181	7,799	8,772	10,073	19,918	19,177	13,062	17,756	20,503
R-squared	0.044	0.045	0.052	0.045	1,441	0.045	0.045	0.055	0.047	0.041

Notes: Standard errors are presented in parentheses and statistical significance is reported as follows: *** p<0.01, ** p<0.05, * p<0.1. All regressions include student fixed effects. Additional controls include dummies for missing values or college average SAT, graduation rate, tuition and fees, and distance from home. Score sends are observed in administrative data and applications come from survey data. Simulated application portfolios have same number of applications of actual portfolio but substitutes observed score sends that did not become an application.

Table 6: Score Sends to Application Conversion - Alternative Explanatory Variables

	Model 1: Score Sends			Model 2: Simulated Application Portfolios			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Student SAT Less College Average SAT	0.0037	--	--	2.5629		--	--
	(0.0085)	--	--	(1.8883)		--	--
Safety	--	-0.0179	--	--	-0.0297	--	--
	--	(0.0174)	--	--	(0.0412)	--	--
Reach	--	-0.0510***	--	--	-0.1055***	--	--
	--	(0.0179)	--	--	(0.0377)	--	--
Average SAT of College (100s)	--	--	0.1601**	--		-0.3266**	--
	--	--	(0.0733)	--		(0.1537)	--
Average SAT of College Squared	--	--	-0.0065**	--		0.0118**	--
	--	--	(0.0029)	--		(0.0059)	--
Minimum Average SAT Among Portfolio	--	--	--	--	--	--	0.0387***
	--	--	--	--	--	--	(0.0056)
Maximum Average SAT Among Portfolio	--	--	--	--	--	--	-0.0777***
	--	--	--	--	--	--	(0.0094)
Observations	10,073	10,073	10,073	20,503	20,503	20,503	20,503
R-squared	0.046	0.047	0.047	0.048	0.049	0.049	0.066

Notes: Standard errors are presented in parentheses and statistical significance is reported as follows: *** p<0.01, ** p<0.05, * p<0.1. All regressions include student fixed effects. Additional controls include dummies for missing values or college average SAT, graduation rate, tuition and fees, and distance from home. Score sends are observed in administrative data and applications come from survey data. Simulated application portfolios have same number of applications of actual portfolio but substitutes observed score sends that did not become an application.

Table 7: Score Sends and Applications to Enrollment Conversion

	Score Send to Enrollment Convsersion	Application to Enrollment Convsersion
College Attributes		
Average SAT (100s)	0.0089	0.0196*
	(0.0061)	(0.0102)
Six-Year Graduation Rate	-0.0015**	-0.0031***
	(0.0006)	(0.0010)
Tuition and Fees ($1,000s)	-0.0007	-0.0014
	(0.0009)	(0.0016)
Distance from Home (100s of miles)	-0.0085***	-0.0051
	(0.0026)	(0.0045)
Distance from Home Squared	0.0028***	0.0015
	(0.0010)	(0.0016)
Instate Public Flagship	0.1226***	0.0612
	(0.0379)	(0.0620)
Instate Public Non-Flagship	0.0210	-0.0132
	(0.0315)	(0.0560)
Instate Private	0.0086	0.0048
	(0.0154)	(0.0245)
Out of State Public	-0.0629***	-0.0659**
	(0.0169)	(0.0285)
First-time Full-time Enrollment (1,000s)	0.0103***	0.0130**
	(0.0033)	(0.0052)
Score Send Attributes		
Free Score Send	0.0243*	0.0483**
	(0.0146)	(0.0234)
Sent Prior to Spring Junior Year (Apr 2013)	-0.0361	0.0443
	(0.0327)	(0.0543)
Sent Spring Junior Year (Apr-Jun 2013)	-0.0582*	0.0053
	(0.0325)	(0.0547)
Sent Summer Prior to Senior Year (Jul-Aug 2013)	-0.0619	-0.0571
	(0.0488)	(0.0791)
Sent Fall Senior Year (Sept-Nov 2013)	-0.0561**	-0.0663
	(0.0276)	(0.0439)
Sent Winter Senior Year (Dec 2013-Jan 2014)	-0.0611**	-0.0532
	(0.0273)	(0.0439)
Applied	No	Yes
Observations	10,073	6,271
R-squared	0.037	0.030

Notes: Notes: Standard errors are presented in parentheses and statistical significance is reported as follows: *** p<0.01, ** p<0.05, * p<0.1. All regressions include student fixed effects. Additional controls include dummies for missing values or college average SAT, graduation rate, tuition and fees, and distance from home. Score sends and enrollment are observed in administrative data and applications come from survey data.

Appendix Table 1: Student Summary Statistics in and out of Sample

	Analytic Sample (N=1,441)		*All High-Achieving Low-Income (N=21,325)*		*All High-Achieving SAT Takers (N=211,712)*		*All SAT Takers (N = 1,087,313)*	
Variable	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*
Male	0.518	0.500	0.529	0.499	0.552	0.497	0.456	0.498
White	0.232	0.423	0.326	0.469	0.595	0.491	0.517	0.500
Black	0.205	0.404	0.063	0.243	0.026	0.159	0.123	0.329
Hispanic	0.266	0.442	0.141	0.349	0.063	0.243	0.170	0.375
Asian	0.269	0.443	0.325	0.468	0.253	0.435	0.131	0.337
Other Race	0.027	0.162	0.145	0.352	0.063	0.242	0.059	0.236
Northeast	0.248	0.432	0.314	0.464	0.290	0.454	0.295	0.456
Midwest	0.087	0.282	0.088	0.283	0.074	0.263	0.053	0.224
South	0.325	0.469	0.333	0.471	0.293	0.455	0.364	0.481
West	0.335	0.472	0.260	0.439	0.233	0.423	0.231	0.421
High School GPA	3.892	0.397	3.908	0.383	3.871	0.386	3.482	0.566
SAT Score	1329	93	1341	96	1359	86	1058	208
SAT Attempts	1.987	0.822	2.086	0.862	2.105	0.874	1.928	0.851
Number of Score Sends	6.994	4.646	7.117	4.664	7.225	4.701	4.995	3.737
Average SAT of Score Sends (100s)	1278	109	1272	140	1276	126	1137	138
Average Distance of Score Sends (100s of Miles)	5.666	5.322	5.358	5.386	5.406	6.004	3.197	5.101

Notes: Sample includes students who took the SAT and sent at least one score send. The analytic sample includes survey takers whereas non-takers were either not offered the survey or did not participate. High-achieving low-income students have a PSAT of at least 125, SAT of at least 1250 and have an estimated family income below $40,000.

Appendix Table 2: Simulated Application Portfolios Examples

Colleges	Received Score Send	Received Application	Simulated College Removed	Simulated College Added	Simulated Portfolio
			Example 1		
A	Yes	Yes	-	-	-
B	Yes	No	A	B	B
C	Yes	No	A	C	C
			Example 2		
A	Yes	Yes	-	-	-
B	Yes	Yes	A	C	B, C
C	Yes	No	B	C	A, C
			Example 3		
A	Yes	Yes	-	-	-
B	Yes	No	A	B	B
C	Yes	No	A	C	C
D	Yes	No	A	D	D
			Example 4		
A	Yes	Yes	A	C	B, C
B	Yes	Yes	A	D	B, D
C	Yes	No	B	C	A, C
D	Yes	No	B	D	A, D
			Example 5		
A	Yes	Yes	A	D	B, C, D
B	Yes	Yes	B	D	A, C, D
C	Yes	Yes	C	D	A, B, D
D	Yes	No	-	-	-

Appendix Table 3: Score Sends to Application Conversion - Using Exact Dates as Expanatory Variable

	Model 1: Score Sends			Model 2: Simulated Application Portfolios		
	(1)	(2)	(3)	(4)	(5)	(6)
College Attributes						
Average SAT (100s)	-0.0056	-0.0057	-0.0050	-0.0279	-0.0272	-0.0260
	(0.0088)	(0.0088)	(0.0088)	(0.0188)	(0.0189)	(0.0189)
Six-Year Graduation Rate	0.0029***	0.0029***	0.0029***	0.0049***	0.0049***	0.0049***
	(0.0008)	(0.0008)	(0.0008)	(0.0019)	(0.0019)	(0.0019)
Tuition and Fees ($1,000s)	-0.0028*	-0.0028*	-0.0028*	-0.0043	-0.0045	-0.0044
	(0.0014)	(0.0014)	(0.0014)	(0.0031)	(0.0031)	(0.0031)
Distance from Home (100s of miles)	-0.0102***	-0.0102***	-0.0101***	-0.0237***	-0.0241***	-0.0236***
	(0.0037)	(0.0037)	(0.0036)	(0.0080)	(0.0080)	(0.0080)
Distance from Home Squared	0.0026*	0.0025*	0.0025*	0.0007**	0.0007***	0.0007**
	(0.0014)	(0.0014)	(0.0013)	(0.0003)	(0.0003)	(0.0003)
Instate Public Flagship	0.0456	0.0462	0.0453	0.1128	0.1081	0.1076
	(0.0523)	(0.0522)	(0.0522)	(0.1185)	(0.1191)	(0.1194)
Instate Public Non-Flagship	0.0331	0.0344	0.0340	0.0298	0.0238	0.0256
	(0.0473)	(0.0472)	(0.0472)	(0.1034)	(0.1039)	(0.1039)
Instate Private	0.0552***	0.0554***	0.0560***	0.0497	0.0466	0.0492
	(0.0199)	(0.0199)	(0.0199)	(0.0449)	(0.0449)	(0.0449)
Out of State Public	-0.1207***	-0.1207***	-0.1216***	-0.2673***	-0.2684***	-0.2693***
	(0.0269)	(0.0269)	(0.0270)	(0.0586)	(0.0589)	(0.0592)
First-time Full-time Enrollment (1,000s)	0.0182***	0.0181***	0.0179***	0.0311***	0.0315***	0.0314***
	(0.0041)	(0.0041)	(0.0041)	(0.0100)	(0.0101)	(0.0101)
Score Send Attributes						
Free Score Send	--	--	-0.0775***	--	--	-0.1031**
	--	--	(0.0242)	--	--	(0.0479)
Date of Score Send (months relative to mean)	0.0118***	0.0098***	0.0033	0.0301***	0.0333***	0.0255***
	(0.0021)	(0.0028)	(0.0033)	(0.0038)	(0.0050)	(0.0065)
Date of Score Send Squared	--	-0.0002	-0.0005	--	0.0003	0.0001
	--	(0.0003)	(0.0003)	--	(0.0003)	(0.0003)
Observations	10,073	10,073	10,073	20,503	20,503	20,503
R-squared	0.040	0.040	0.042	0.045	0.045	0.046

Notes: Standard errors are presented in parentheses and statistical significance is reported as follows: *** p<0.01, ** p<0.05, * p<0.1. Student characteristic controls include sex and ethnicity dummies, student SAT and number of SAT attempts, and high school GPA. Additional controls in all regressions include dummies for missing values or college average SAT, graduation rate, tuition and fees, and distance from home. Score sends are observed in administrative data and applications come from survey data. Simulated application portfolios have same number of applications of actual portfolio but substitutes observed score sends that did not become an application.

Appendix Table 4: Score Sends to Application Conversion - Model 1 (Independent Applications)

	Model 1: Score Sends, Student Fixed Effects						
	All	Apps Missing Score Sends < 6	Apps Missing Score Sends < 5	Apps Missing Score Sends < 4	Apps Missing Score Sends < 3	Apps Missing Score Sends < 2	Apps Missing Score Sends = 0
College Attributes							
Average SAT (100s)	-0.0057	-0.0052	-0.0066	-0.0033	-0.0051	-0.0153	-0.0221
	(0.0087)	(0.0089)	(0.0089)	(0.0092)	(0.0098)	(0.0109)	(0.0147)
Six-Year Graduation Rate	0.0030***	0.0029***	0.0030***	0.0024***	0.0026***	0.0030***	0.0019
	(0.0008)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0010)	(0.0013)
Tuition and Fees ($1,000s)	-0.0030**	-0.0031**	-0.0032**	-0.0024	-0.0015	-0.0010	0.0020
	(0.0014)	(0.0015)	(0.0015)	(0.0015)	(0.0016)	(0.0017)	(0.0024)
Distance from Home (100s of miles)	-0.0102***	-0.0097***	-0.0106***	-0.0115***	-0.0093**	-0.0051	-0.0007
	(0.0036)	(0.0037)	(0.0038)	(0.0039)	(0.0041)	(0.0043)	(0.0061)
Distance from Home Squared	0.0026*	0.0026*	0.0031**	0.0035**	0.0027*	0.0014	-0.0004
	(0.0013)	(0.0014)	(0.0014)	(0.0014)	(0.0015)	(0.0016)	(0.0023)
Instate Public Flagship	0.0364	0.0317	0.0225	0.0476	0.0726	0.1046	0.1991**
	(0.0522)	(0.0535)	(0.0543)	(0.0550)	(0.0581)	(0.0637)	(0.0853)
Instate Public Non-Flagship	0.0259	0.0212	0.0140	0.0337	0.0616	0.0897	0.1721**
	(0.0472)	(0.0483)	(0.0489)	(0.0500)	(0.0526)	(0.0574)	(0.0787)
Instate Private	0.0549***	0.0573***	0.0571***	0.0579***	0.0717***	0.0819***	0.0823**
	(0.0198)	(0.0201)	(0.0203)	(0.0209)	(0.0220)	(0.0241)	(0.0325)
Out of State Public	-0.1292***	-0.1334***	-0.1346***	-0.1203***	-0.1062***	-0.1070***	-0.0806*
	(0.0269)	(0.0272)	(0.0275)	(0.0283)	(0.0299)	(0.0329)	(0.0439)
First-time Full-time Enrollment (1,000s)	0.0176***	0.0177***	0.0185***	0.0188***	0.0157***	0.0153***	0.0161**
	(0.0041)	(0.0041)	(0.0042)	(0.0043)	(0.0046)	(0.0051)	(0.0067)
Score Send Attributes							
Free Score Send	-0.0584**	-0.0631***	-0.0688***	-0.0732***	-0.0815***	-0.0747***	-0.0938**
	(0.0234)	(0.0230)	(0.0231)	(0.0236)	(0.0252)	(0.0275)	(0.0393)
Sent Prior to Spring Junior Year (Apr 2013)	-0.0791*	-0.0999**	-0.0926**	-0.0784*	-0.0812	-0.0749	-0.0721
	(0.0447)	(0.0456)	(0.0462)	(0.0471)	(0.0503)	(0.0545)	(0.0737)
Sent Spring Junior Year (Apr-Jun 2013)	-0.0747	-0.0871*	-0.0862*	-0.0806	-0.0875*	-0.1019*	-0.0093
	(0.0465)	(0.0477)	(0.0485)	(0.0490)	(0.0521)	(0.0572)	(0.0832)
Sent Summer Prior to Senior Year (Jul-Aug 201	0.0202	0.0056	0.0070	0.0272	0.0382	0.0277	0.0858
	(0.0551)	(0.0556)	(0.0561)	(0.0584)	(0.0616)	(0.0671)	(0.0919)
Sent Fall Senior Year (Sept-Nov 2013)	0.0762**	0.0626*	0.0624*	0.0694*	0.0674*	0.0566	0.1310**
	(0.0343)	(0.0354)	(0.0363)	(0.0367)	(0.0394)	(0.0432)	(0.0560)
Sent Winter Senior Year (Dec 2013-Jan 2014)	0.0197	0.0063	0.0075	0.0115	0.0056	-0.0046	0.0628
	(0.0346)	(0.0357)	(0.0366)	(0.0371)	(0.0402)	(0.0433)	(0.0565)
Observations	10,073	9,592	9,332	8,772	7,926	6,433	3,438
R-squared	0.046	0.046	0.046	0.045	0.044	0.044	0.057

Notes: Standard errors are presented in parentheses and statistical significance is reported as follows: *** p<0.01, ** p<0.05, * p<0.1. Student characteristic controls include sex and ethnicity dummies, student SAT and number of SAT attempts, and high school GPA. Additional controls in all regressions include dummies for missing values or college average SAT, graduation rate, tuition and fees, and distance from home. Score sends are observed in administrative data and applications come from survey data. Simulated application portfolios have same number of applications of actual portfolio but substitutes observed score sends that did not become an application.

Appendix Table 5: Score Sends and Applications to Enrollment Conversion
Condtional logistic model (odds ratios)

	Simulated Application Portfolio	*Score Send to Enrollment Convsersion*	*Application to Enrollment Convsersion*
College Attributes			
Average SAT (100s)	0.7435*	1.1036*	1.1434**
	(0.1178)	(0.0653)	(0.0775)
Six-Year Graduation Rate	1.0429***	0.9863***	0.9807***
	(0.0140)	(0.0052)	(0.0060)
Tuition and Fees ($1,000s)	0.9703	0.9909	0.9868
	(0.0232)	(0.0094)	(0.0113)
Distance from Home (100s of miles)	0.6999***	0.9229***	0.9667
	(0.0555)	(0.0243)	(0.0287)
Distance from Home Squared	1.0106***	1.0244**	1.0093
	(0.0029)	(0.0101)	(0.0112)
Instate Public Flagship	1.5378	1.5877	1.0763
	(1.2917)	(0.5112)	(0.4209)
Instate Public Non-Flagship	1.1264	1.0549	0.7955
	(0.8630)	(0.3130)	(0.2879)
Instate Private	1.2902	1.1097	1.0367
	(0.5415)	(0.1542)	(0.1631)
Out of State Public	0.0389***	0.5145***	0.5767**
	(0.0213)	(0.0975)	(0.1259)
First-time Full-time Enrollment (1,000s)	1.2564***	1.0880***	1.0829**
	(0.0915)	(0.0293)	(0.0335)
Score Send Attributes			
Free Score Send	0.2849***	1.3045*	1.4212**
	(0.1332)	(0.1973)	(0.2462)
Sent Prior to Spring Junior Year (Apr 2013)	1.6558	0.7659	1.3302
	(3.0244)	(0.2150)	(0.4425)
Sent Spring Junior Year (Apr-Jun 2013)	3.9677	0.6039*	1.0489
	(7.6324)	(0.1775)	(0.3807)
Sent Summer Prior to Senior Year (Jul-Aug 2	31.1095	0.5726	0.7110
	(65.5720)	(0.2301)	(0.3273)
Sent Fall Senior Year (Sept-Nov 2013)	262.3752***	0.6109**	0.6507
	(499.0570)	(0.1356)	(0.1706)
Sent Winter Senior Year (Dec 2013-Jan 201	426.7210***	0.5502***	0.6733
	(828.0022)	(0.1240)	(0.1792)
Applied	Yes	No	Yes
Observations	20,503	8,436	4,870
Pseudo R-squared	0.0797	0.0612	0.0443

Notes: Standard errors are presented in parentheses and statistical significance is reported as follows: *** p<0.01, ** p<0.05, * p<0.1. Effects are interpreted as the multiple by which the probability favoring attendance at college j is multiplied with a one-unit increase in that variable. Figures greater than one are considered positive effects. Additional controls include dummies for missing values or college average SAT, graduation rate, tuition and fees, and distance from home. Score sends and enrollment are observed in administrative data and applications come from survey data.

Appendix Table 6: Simulated Application Portfolio Conversion, Heterogeneous Effects

	Male	*Female*	*White or Asian*	*Black or Hispanic*
College Attributes				
Average SAT (100s)	-0.0185	-0.0356	-0.0238	-0.0144
	(0.0253)	(0.0280)	(0.0245)	(0.0316)
Six-Year Graduation Rate	0.0072***	0.0017	0.0048*	0.0047
	(0.0024)	(0.0028)	(0.0025)	(0.0029)
Tuition and Fees ($1,000s)	-0.0077*	0.0016	-0.0064	-0.0046
	(0.0042)	(0.0048)	(0.0043)	(0.0045)
Distance from Home (100s of miles)	-0.0366***	-0.0173	-0.0309***	-0.0180
	(0.0115)	(0.0115)	(0.0108)	(0.0124)
Distance from Home Squared	0.0011***	0.0006	0.0009**	0.0006
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Instate Public Flagship	-0.0432	0.3625*	0.1222	0.0307
	(0.1569)	(0.1873)	(0.1696)	(0.1634)
Instate Public Non-Flagship	-0.0875	0.2240	0.0835	-0.0698
	(0.1373)	(0.1583)	(0.1428)	(0.1460)
Instate Private	-0.0342	0.1076*	0.0852	0.0228
	(0.0624)	(0.0633)	(0.0619)	(0.0662)
Out of State Public	-0.3402***	-0.1551*	-0.2853***	-0.2838***
	(0.0803)	(0.0877)	(0.0835)	(0.0821)
First-time Full-time Enrollment (1,000s)	0.0361***	0.0213	0.0200	0.0478***
	(0.0134)	(0.0152)	(0.0141)	(0.0144)
Score Send Attributes				
Free Score Send	0.0177	-0.1393**	-0.0622	-0.0622
	(0.0644)	(0.0639)	(0.0689)	(0.0573)
Sent Prior to Spring Junior Year (Apr 2013)	-0.0952	0.6332	-0.0272	0.1925
	(0.1632)	(0.5948)	(0.2123)	(0.2285)
Sent Spring Junior Year (Apr-Jun 2013)	-0.0623	0.6311	-0.1067	0.2686
	(0.1733)	(0.5960)	(0.2185)	(0.2300)
Sent Summer Prior to Senior Year (Jul-Aug 2013)	0.3543	0.5810	0.2154	0.4544*
	(0.2187)	(0.6092)	(0.2383)	(0.2672)
Sent Fall Senior Year (Sept-Nov 2013)	0.3010*	0.8984	0.3181	0.5146**
	(0.1752)	(0.5935)	(0.2194)	(0.2237)
Sent Winter Senior Year (Dec 2013-Jan 2014)	0.3793**	0.8735	0.3224	0.5715**
	(0.1790)	(0.5955)	(0.2237)	(0.2304)
Sent Late Senior Year (After Jan 2014)	0.3731*	1.0068	0.5091**	0.5313**
	(0.2091)	(0.6123)	(0.2448)	(0.2547)
Observations	10,180	10,323	9,799	10,012
R-squared	0.058	0.044	0.066	0.039

Notes: Standard errors are presented in parentheses and statistical significance is reported as follows: *** p<0.01, ** p<0.05, * p<0.1. All regressions include student fixed effects. Score sends are observed in administrative data and applications come from survey data. Simulated application portfolios have same number of applications of actual portfolio but substitutes observed score sends that did not become an application.