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Does Opting Into a Search Service Provide Benefits to Students?

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Abstract

Recent research suggests that the use of student search services is an effective part of a college's student marketing and recruitment strategy. What is not clear, however, is whether participating in a search service is an effective part of a student's college search strategy. To address this question, we exploit a recent change in the choice architecture that structures students' decision to participate in ACT's Educational Opportunity Service (EOS) in order to make a causal inference about the benefit to the student of opting into a search service. We hypothesized that students who had opted into EOS unintentionally sent scores to more colleges than students who opted out. Indeed, we found that unintentional opt-in was associated with an 8% increase in the odds of sending scores to any colleges, and for students who sent scores, unintentional EOS opt-in was associated with a 1.1 increase in the number of colleges to which scores were sent. Results of this study support the hypothesis that EOS opt-in may indeed be an effective part of a student's college search strategy.

Keywords: Consideration Set, College Choice, Propensity Score Methods

Does Opting Into a Search Service Provide Benefits to Students?

Each year, roughly 3 million first-time, first-year, degree-seeking undergraduates begin their college education at one of over 4,000 degree-granting postsecondary institutions within the United States (National Center for Education Statistics, 2017). From a strategic enrollment management perspective, one of the goals each year for a college is to matriculate an optimal number of these students while getting the desired mix of student characteristics to ensure an academically engaging and diverse learning community (Hossler, Kalsbeek, & Bontrager, 2015). To achieve this goal, colleges must first identify a pool of prospective students and then tailor their recruitment and marketing efforts toward providing personalized information that can assist these students in their movement through the various stages of the admissions funnel. In the earliest stage of this funnel, admissions offices are focused on increasing their brand awareness and recognition among prospective students in order to convert many of them to inquiries.

One of the primary ways in which colleges identify prospective students is through student search services such as ACT's Educational Opportunity Service (EOS), the College Board's Student Search Service, and the services of the National Research Center for College and University Admissions (NRCCUA). Through these search services, colleges can select specific search criteria to identify prospective students using combinations of their geographic (e.g., state, zip code), academic (e.g., test score ranges, grades, major), demographic (e.g., race/ethnicity, gender), and socioeconomic (e.g., family income, parents' education) characteristics. Colleges can then purchase the names and contact information of students within these different market segments in order to send them targeted marketing and recruitment messages.

Recent evidence from a survey of four-year colleges by Ruffalo Noel Levitz (2016a) suggests that colleges' use of search services is both wide-ranging and effective. Regarding the use of search services, many colleges tend to purchase student names from multiple sources simultaneously in order to cast the widest net possible for prospective students. For example, 51% of private colleges and 40% of public colleges responding to the survey use three or more search services in a given year to acquire the names and contact information of high school juniors. The volume of prospective student names purchased by colleges is also quite extensive. Among the respondents to the survey, the median number of prospective student names purchased by private colleges is 65,000, with the middle 50% purchasing between 30,000 and 130,000 student names. Among public colleges, the median number of student names purchased is 75,000, with the middle 50% purchasing between 37,500 and 120,000 student names.

Regarding the effectiveness of using search services to assist colleges in getting prospective students into their admissions funnel, respondents to the Ruffalo Noel Levitz survey (2016a) report that purchased names are the leading source of high school student inquiries for the college. Among public four-year colleges, the median share of inquiries that come from purchased names is 20%, with the middle 50% of these colleges reporting that purchased names made up between 10% and 48% of their inquiries. Among private four-year colleges, the median share of inquiries from purchased names was 24%, with the middle 50% of these colleges reporting that purchased names made up between 10% and 46% of their inquiries. These results lead institutions themselves to conclude that conducting student searches via email campaigns is one of the ten most popular electronic recruiting activities among four-year institutions (Ruffalo Noel Levitz, 2016b).

The evidence just cited suggests that the use of student search services is an effective part of a college's student marketing and recruitment strategy. What is not clear, however, is whether participating in a search service is an effective part of a student's college search strategy. Participating in a search service allows students to be contacted by schools and scholarship agencies wishing to provide information and recruitment materials. Previous studies have shown that students who receive more information and guidance about the college application and enrollment process tend to take steps toward college enrollment, such as completion of the Free Application for Federal Student Aid (FAFSA), at higher rates (Bettinger, Long, Oreopoulos, & Sanbonmatsu, 2012) and to enroll in college at higher rates (Plank & Jordan, 2001). It is assumed that students who are more informed are more likely to enroll at a school that is a better fit for their academic achievement level and preferences, and research has shown that students attending a college that is a good fit are more likely to persist (ACT, 2014a) and more likely to complete a degree in a timely manner (Howell, Pender, & Kumar, 2016).

Whether or not students receive some benefit from participating in a search service is an important policy question; although student participation in a search service is optional, it requires students to consent to the release of their personal information to interested colleges and scholarship agencies. In an era of heightened scrutiny over how individuals' personal information is shared among and used by those entities that collect it routinely, having empirical evidence that speaks to the personal benefits of participating in a search service could help to better inform students about the potential tradeoffs associated with opting into such a service.

For this study, we hypothesize that participating in a search service will benefit students by increasing their awareness of specific college opportunities that may not have been previously under their consideration. Under this hypothesis, we would expect that the students who

participate in a search service would have a larger college consideration set than they would have had in absence of their participation in the service. We will address this hypothesis using data from students who have taken the ACT on a national test date and who have elected either to opt into or out of ACT's Educational Opportunity Service.

Causal Framework

Although it is an important policy question, the causal effect of participating in a search service on the size of the students' consideration set is difficult to isolate. According to the Rubin Causal Model (Holland, 1986), a necessary condition for causality is that a treatment is applied to an individual at a particular point in time. This condition for causality assumes that at the point in time the treatment is received the individual could have otherwise been subjected to some alternative treatment or no treatment (i.e., control). For each of these actions (treatment or control), there is a potential outcome for the individual. The causal effect of the treatment on the individual is defined as the difference between the potential outcome under the treatment and the potential outcome under the control. For this study, these two potential outcomes can be written as follows:

$$\textit{potential outcome} = \begin{cases} Y_{1i} & \text{if SEARCH}_i = 1 \\ Y_{0i} & \text{if SEARCH}_i = 0 \end{cases}$$

The fundamental problem with inferring a causal effect is that for any particular individual we can observe only one of the potential outcomes—either under the treatment or under the control. We cannot know what the outcome of a search service participant would have been had the student not participated in the service. Likewise, we cannot know what the outcome of a non-participant would have been had the student participated in the search service. A

common approach to address this missing data problem is to examine the difference in the observed outcomes between individuals who received the treatment and those who received the control. The relationship between this difference in observed outcomes and the causal effect can be expressed as follows:

$$\underbrace{E\left[\mathrm{Y}_i \,\middle|\, \mathrm{SEARCH}_i = 1\right] - E\left[\mathrm{Y}_i \,\middle|\, \mathrm{SEARCH}_i = 0\right]}_{\text{Observed difference in postsecondary opportunity}} = \underbrace{E\left[\mathrm{Y}_{1i} \,\middle|\, \mathrm{SEARCH}_i = 1\right] - E\left[\mathrm{Y}_{0i} \,\middle|\, \mathrm{SEARCH}_i = 1\right]}_{\text{average EOS effect on the participants}} + \underbrace{E\left[\mathrm{Y}_{0i} \,\middle|\, \mathrm{SEARCH}_i = 1\right] - E\left[\mathrm{Y}_{0i} \,\middle|\, \mathrm{SEARCH}_i = 0\right]}_{\text{selection bias}}$$

such that the observed difference in the average outcome between search service participants and non-participants is equal to the average effect of the search service on those who participated plus some degree of selection bias. Selection bias is represented as the difference in the average outcome under conditions of the control (i.e., not participating in the search service) between search service participants and non-participants. If selection bias is negative, search service participants would have fared worse than non-participants in absence of the search service; this means that the observed difference in the outcome between the two groups underestimates the effect of the search service. Conversely, if selection bias is positive, search service participants would have fared better than non-participants in absence of the search service; this means that the observed difference in the outcome between the two groups overestimates the effect of the search service. If selection bias is zero, search service participants would have fared the same as non-participants in absence of the search service, and the observed difference is thus equivalent to the effect of the search service on its participants.

Regardless of whether it results in an underestimation or an overestimation of the treatment effect, selection bias is present in the observed difference between participants and

non-participants when assignment to the treatment is not independent of the outcome. One way to ensure independence between treatment assignment and the outcome—and thus solve the selection bias problem—is to randomly assign units to the treatment. This type of assignment found in a randomized controlled trial provides some assurance that the control and treatment groups are balanced—meaning that the characteristics of these two groups are equivalent—prior to the treatment. Students who participate in a search service, however, are not selected at random; they opt into or out of the search service because of the potential outcome (whether realized or not) that they associate with their participation in the search service. Thus our observed differences in outcomes between participants and non-participants will be subject to some degree of selection bias.

Since students opt into as opposed to being randomly assigned to the search service, a goal of our study is to create a research design that best approximates a randomized controlled trial in order to achieve equivalent groups between participants and nonparticipants. To achieve this, we will exploit a recent change in the choice architecture that structures the students' decision to participate in ACT's Educational Opportunity Service (EOS) in order to make a causal inference about the benefit to the student of opting into a search service.

Students who take the ACT face the EOS participation decision at the time that they register for the test. Historically, the EOS choice architecture that appeared on the paper registration form posed the students' decision as an active choice whereby students could fill in either the "Yes" or "No" response option to indicate their decision. Students' names were included within EOS if they selected "Yes," and their names were excluded from the service if they either selected "No" or elected not to respond to the question. Beginning with the introduction of online registration in the 2007-08 test year, ACT changed the EOS choice

architecture so that opting into the service was the default. The participation decision was then worded as the statement “I would like to receive information from colleges and scholarship agencies about educational, scholarship, career, and financial aid opportunities” with a checkbox that had been pre-populated with a checkmark. In this format, students needed to take no action in order to opt into EOS. Students were required to uncheck the box by the statement to opt out of the service. Electing not to respond to the item was equivalent to opting into EOS. The EOS opt-in rate increased by 11 percentage points the year in which this change to the choice architecture was implemented (See Figure 1). In the 2014-15 test year, ACT reverted back to the former EOS choice architecture where the students’ participation decision was posed as an active choice with “Yes” and “No” response options. After reverting back to the old EOS choice architecture, the rate at which students opted into EOS immediately fell by 9 percentage points.

The substantial changes in the EOS opt-in rates that followed the changes to the choice architecture for the EOS participation decision provide some evidence that the use of a default is an effective means of achieving a desired response. Thaler and Sunstein (2008) argue that defaults are effective because they capitalize on a bias in the way that people think, known as the status quo bias. Under this bias, individuals tend to stick with the current state of affairs because of inattentiveness or the perceived (or actual) amount of effort necessary to change the current state of affairs. Although unchecking the default in order to opt out of EOS does not require much effort on the part of students, inattentiveness may have been a contributing factor to the increase in the EOS opt-in rate under the default. In particular, the EOS participation decision is one item among hundreds of items included as part of a lengthy registration process; whereas other items in the registration process require a response, the EOS item was among a set of questions in which responses were encouraged but not required. Given this scenario, it is likely

that some students were inattentive to the item and likely unaware that they were opting into EOS.

For this study, we exploit this change in the EOS choice architecture to create two groups for comparison—an "unintentional" opt-in group and an intentional opt-out group. To create these two groups, we first estimate the likelihood of opting into EOS under the active choice framing to predict out-of-sample which students under the default choice framing would have had a high probability of opting into EOS had they registered under the active choice framing. We then select for analysis only those students under the default choice framing who have a low probability of opting into EOS under the active choice framing. For the purpose of this study, we refer to the subsample of these students who opted out under the default choice framing as "intentional opt-outs" and we refer to the subsample of these students who opted in under the default choice framing as "unintentional opt-ins." We then balance these two groups statistically on the students' propensity to opt in under the active choice framework as well as on other background characteristics (e.g., academic achievement, race/ethnicity, and gender) known to be related to postsecondary educational opportunity.

Sample

This study used student data from two ACT-tested high school graduating classes, local demographic data from the United States Census Bureau (www.factfinder.census.gov), and first-year college enrollment data from the National Student Clearinghouse (www.studentclearinghouse.org). Our study focused primarily on students in the ACT-tested graduating class of 2014 (N = 1,845,787), as these students were exposed to the default choice framing for EOS where nonresponse was an implied opt-in. To identify "unintentional opt-ins" among this group, we used ACT data from students in the graduating class of 2016 (N =

2,090,342), as they were exposed to the active choice framing for EOS where nonresponse was an implied opt-out.

Samples were limited to U.S. students who tested during a national test date and who registered to take the ACT using the online registration system. More than 99% of students testing on a national test date register online; very few students register using a paper registration form. Students who tested as part of state- or district-funded testing were excluded from the analyses because these students used a paper answer document to opt in or opt out of EOS rather than the online registration system; therefore, the policy change was irrelevant for these students.

Samples were also limited to students who first tested during their junior year of high school. This ensures that each cohort only tested under one policy and that students who opted into EOS were likely to be in the pool of interest for participating institutions (students' names are much more likely to be purchased by institutions if the students first tested during their junior year rather than their senior year).

Students were categorized as "Opt-In" if they opted into EOS one or more times during their junior year of high school. Students who tested more than once may have opted in on one occasion and opted out on another; these students would still be exposed to the benefits of EOS for the test event in which they opted in. It is further assumed that the group of students who opted in on one occasion and opted out on another are more likely to include those students who unintentionally opted in and may have intentionally opted out on a subsequent test event. Students were excluded from the sample if they opted out of EOS during their junior year of high school but opted in during their senior year of high school because it is possible that these students' names were purchased through EOS, and as such would add noise to the sample.

After excluding students for the aforementioned reasons, our final sample from the ACT-tested graduating class of 2014 had 594,773 students, representing 32% of the tested population, and our final sample from the ACT-tested graduating class of 2016 had 534,439 students, representing 26% of the tested population.

Covariates

There are many factors that are likely related to both the student's probability of opting into a search service and the size of their college consideration set, including academic achievement, student demographics, educational aspirations, preferences, and other college preparatory behaviors (ACT, 2013; 2014b). For this study, we include ACT Composite scores as a measure of academic achievement; gender, race/ethnicity, parent income, parent education, type of high school attended, region of residence, and statewide ACT participation rate as measures of student demographics; degree aspirations and planned major as measures of educational aspirations; preferred college type and preferred college location as measures of student preferences; and number of times a student takes the ACT as a measure of student college preparatory behavior.

A full list of the covariates can be found in Table 2. Many of the variables in this study were coded as dummy variables due to their categorical nature, although there are a few exceptions. The number of times a student took the ACT, the ACT statewide participation rate (defined as the percent of the high school graduating class within each state who took the ACT), and the students' ACT Composite score are numeric. Also included in the model predicting EOS opt-in is the squared ACT Composite score, which allows us to account for the non-linear relationship between EOS opt-in and academic achievement such that students with moderate

ACT scores are more likely to opt into EOS and students with extremely low or high scores are less likely to opt in.

Outcome

For the purpose of this study, we operationalize the size of the students' consideration set as the number of institutions to which the students sent their ACT scores, as score sending is often viewed by colleges as a form of inquiry among prospective students.

Census Data

To account for missing self-reported income and parent educational attainment information within ACT data, additional information was obtained from the United States Census Bureau (www.factfinder.census.gov). For each state plus Washington, D.C., the data of interest were 5-year American Community Survey estimates from 2015 at the census block group and zip code levels. Variables included educational attainment for the population 25 years and over and household income in the past 12 months (in 2015 inflation-adjusted dollars). Students were matched to the census data at the most granular level available, first by census block group, or if census block group was unavailable, by zip code. Census data were matched for more than 99% of the students.

Methods

To provide some context for our model, the first set of analyses compares students who tested under the default choice framing to students who tested under the active choice framing. Descriptive statistics were employed to compare student characteristics before and after the policy change.

To exploit the policy change, a second set of analyses used the EOS participation decision of students under the active choice framing to predict the participation decision of

students under the default choice framing. Inverse propensity score weights were then used to balance potential group differences in both samples. All analyses were conducted using SAS statistical software.

Out-of-Sample Prediction for Default Choice

A logistic regression model was created predicting EOS opt-in for the graduating class of 2016, as these students registered under the active choice framing policy. Student demographic information, ACT scores, number of times students took the ACT, college aspirations and preferences, parents' education and income, and census data were included as covariates. Descriptive statistics for the covariates included in the regression analysis can be found in Table 2, and the results of this model can be found in Table 3.

The estimated intercept and slope parameters from the model were applied to the sample from the graduating class of 2014, who registered under the default choice framing policy, to obtain their estimated probability of opting into EOS under the active choice framing policy. From this sample of students under the default choice framing, students with a low estimated probability of opting into EOS under the active choice framing were retained as the analysis sample. Multiple definitions of "low estimated probability" were examined (0.5, 0.6, and 0.7), taking into account baseline EOS opt-in rates and propensity score distributions. Students with a low estimated probability of opting into EOS under the active choice policy who did in fact opt into EOS under the default choice policy were classified as "unintentional opt-ins," and students with a low estimated probability of opting into EOS under the active choice policy who did not opt into EOS under the default choice policy were classified as "intentional opt-outs."

Inverse Propensity Score Weighting

Using the sample of students from the graduating class of 2014 with a low estimated probability of opting into EOS under the active choice framework, we estimated another logistic model predicting EOS opt-in to obtain inverse propensity score weights to balance our unintentional opt-in and intentional opt-out samples. Covariates included student demographic information, ACT scores, number of times students took the ACT, college aspirations and preferences, parents' education and income, census data, and the predicted probability of opting into EOS derived from the active choice policy logistic regression model. The predicted probability of opting into EOS derived from the active choice policy model was included in the prediction model as a proxy for motivation to participate in the search service to ensure that the model is robust to differences in the predicted probabilities. A full list of covariates and the results of this model can be found in Table 4. Weighted means were compared for the opt-ins and opt-outs to ensure that balance was achieved, and can be found in Table 5. These samples and the resulting inverse propensity score weights were used for the final analyses.

Propensity score weighting is a method developed to take into account differences in non-random treatment and control groups, where in this study, the treatment is opting into EOS and the control is opting out. A propensity score is the probability that an individual has been exposed to a treatment, taking into account relevant covariates. These scores can be used to create balanced treatment and control group samples where individuals are matched on the basis of their propensity scores, and therefore are also matched on the set of covariates (Rosenbaum & Rubin, 1983). Prior research has shown that students with higher degree aspirations, students whose parents have lower income and education levels, and students who self-report their race/ethnicity as African American or Hispanic opt into EOS at higher rates (ACT, 2014b).

Propensity scores are used to assign inverse propensity score weights to balance differences between groups such that the weighted distributions of covariates are the same in each group. Unlike propensity score matching, this allows us to include more observations in each sample rather than discarding observations that cannot be matched. The primary outcome of interest in this study is the effect of the treatment on the treated individuals; therefore, weights are created to balance the control group toward the treatment group rather than balancing both groups toward the population average (Hirano and Imbens, 2001; Ho, Imai, King, & Stuart, 2007; Ridgeway, 2006). Inverse propensity score weights are assigned such that for students who opted into EOS, the weights are assigned to 1, and for students who opted out of EOS, the weights are assigned to p / (1-p), where p is the propensity score for that student.

Outcome Analyses

The size of the students' consideration set, defined here as the number of colleges where students sent scores, was modeled using a zero-inflated negative binomial model. A zero-inflated negative binomial model was used because number of scores sent is a count variable with variance greater than the mean and a large proportion of zeros. Multiple models were considered, including Poisson, negative binomial, zero-inflated Poisson, and zero-inflated negative binomial. Results were virtually identical across the four models, but the zero-inflated negative binomial model had the best fit of the four models considered. Predictors included EOS opt-in, student covariates, census data, and the predicted probability of opting into EOS derived from the 2016 logistic regression model. A full list of the covariates included in the analysis can be found in Table 10. The probability of excess zeros was modeled using a logistic link function and the probability of a count was modeled using a negative binomial function. The negative binomial dispersion parameter was estimated with maximum likelihood. All of the covariates in the

negative binomial model were included in the zeros model, because many of the covariates are related to the number of scores sent and/or to whether a student sends any scores.

Results

Evaluation of match to census data

More than 99.5% of records were matched to census data for both the 2014 and 2016 data samples. A comparison between the characteristics of matched and non-matched students can be found in Table 1. For both samples, based on students' self-reported responses when registering for the ACT, records that were not matched to census data were more likely to come from households with lower incomes (by 4-6 percentage points) and less likely to come from households with higher incomes (by 7-9 percentage points). Unmatched students were also more likely to report their race/ethnicity as African American (by 5-6 percentage points) and less likely to report their race/ethnicity as White (by 13-15 percentage points). Unmatched students were more likely to reside in the South (by 8-14 percentage points) or West (by 9-10 percentage points) and less likely to reside in the Midwest (by 14-22 percentage points) or Northeast (by 1-2 percentage points). Unmatched students scored on average about three-quarters of one point less on the ACT compared to students who were matched to census data.

Characteristics of Students Before and After Policy Change

Characteristics of students under the default choice policy (2014) and under the active choice policy (2016) can also be found in Table 1 (in the matched sample columns). Under the default choice policy, 89% of students opted into EOS, while under the active choice policy, 74% of students opted into EOS. The matched samples were otherwise similar with respect to average ACT Composite scores and student demographics.

Active Choice Policy Data Sample for Estimating Intention to Opt Into EOS

The active choice policy data sample (N = 534,439) was used to estimate whether students in the default choice policy data sample had opted in intentionally or unintentionally. A logistic regression model was used to estimate the probability of opting into EOS in the active choice policy sample. Results of the logistic regression model can be found in Table 3. The resulting probabilities in the sample ranged from 0.17 to 0.97 for students who opted into EOS, and 0.12 to 0.97 for students who opted out. The range of probabilities are not considered extreme and therefore no observations were excluded from the analysis.

Development of Analysis Sample

The parameter estimates of the logistic regression model developed with the active choice policy sample were used to calculate the probability of the default choice policy sample opting into EOS under the active choice policy. The resulting probabilities ranged from 0.16 to 0.98 for students who opted into EOS and 0.16 to 0.96 for students who opted out, indicating a reasonable support for both groups.

In order to classify students as intentional opt-outs and unintentional opt-ins, we focused on students with a low predicted probability of opt-in based on the active choice model. Several definitions of “low predicted probability” were explored, taking into account the overall opt-in rate and the distribution of probabilities (EOS opt-in rates were 89% under the default choice policy and 74% under the active choice policy). Results for our outcome model were nearly identical when we set the cutoffs for defining unintentional opt-in at 0.5, 0.6, and 0.7, suggesting that the effect of being in the unintentional opt-in group on the outcome is robust to the choice of cutoff. Therefore, the rest of this paper focuses on the 0.5 cutoff. Students from the default choice policy sample who had a predicted probability of opting into EOS under the active choice

policy that was less than 0.5 were retained for analysis. Of these students, those who opted into EOS were classified as “unintentional opt-ins” and those who opted out of EOS were classified as “intentional opt-outs.” The final analysis sample contains 43,153 students, including 28,532 students who opted into EOS (66%) and 14,621 students who opted out of EOS (34%).

A logistic regression model was used to create inverse propensity score weights for the analysis sample. Results of the logistic regression model are in Table 4. Table 5 contains the unweighted and weighted means of the covariates for the analysis sample. As can be seen in the table, there were differences in the mean values of many of the covariates of students who opted into EOS compared to those who did not opt in, and the differences largely disappear for the weighted means.

Representativeness of Students in the Analysis Sample

Table 6 compares demographic information of students in the full ACT-tested graduating class of 2014 (N = 1,845,787), the cleaned 2014 data sample used to create the analysis sample (N = 594,773), and the 2014 analysis sample (N = 43,153). Students in the analysis sample tended to have higher ACT Composite scores, lower EOS opt-in rates, and were much more likely to have missing self-reported parent income. The analysis sample also contained a much larger percentage of White students and much lower percentages of African American and Hispanic students. This makes sense because, as Table 7 shows, African American and Hispanic students also have some of the highest EOS opt-in rates and as a result were more likely to have high predicted probabilities of opting into EOS. It is expected that because African American and Hispanic students opt into EOS at such high rates, few would be likely to have opted into EOS unintentionally.

To further explore the low percentages of African American and Hispanic students in the analysis sample, a post-hoc analysis was conducted comparing the EOS opt-in rates by race/ethnicity across several years of ACT-tested students before and after the opt-in policy change. Table 8 contains the EOS opt-in rates of all students who took the ACT during the 2012-2013 to 2015-2016 school years, by race/ethnicity (note that these data are different populations of students than the ACT-tested high school graduating classes of 2014 and 2016 that are the main focus of this study; therefore, the EOS opt-in rates in Table 8 do not match the results in Table 7). As shown in Table 8, the drop in EOS opt-in rates after the policy change was greater for White students than for African American and Hispanic students. The EOS opt-in rates of White students dropped by 16 percentage points between 2014 and 2016, whereas during the same time period, the drop in EOS opt-in rates were only 8 percentage points for African American students and 9 percentage points for Hispanic students. This indicates that White students had a disproportionate response to the policy change. Because of the high opt-in rates for African American and Hispanic students, we believe that the over-representation of White students in the analysis sample, while a limitation of the generalizability of this study to other demographic groups, is representative of the demographic makeup of students who were likely to unintentionally opt into EOS.

Predicting Size of the Consideration Set

Overall, students who opted into EOS sent more scores (4.7), on average, than students who did not opt in (unweighted mean 4.6, weighted mean 4.3). The number of colleges where students sent scores is a count variable with variance greater than the mean and a large proportion of zeros. Students sent scores to an average of 4.7 colleges, with a variance of 21.9. The modal number of scores sent was zero, with 28% of students sending scores to zero colleges,

and the maximum number of scores sent was 40, with one student sending scores to 40 colleges. Figure 2 contains the frequency distribution of the number of scores sent in the analysis sample.

Multiple models were considered, including Poisson, negative binomial, zero-inflated Poisson, and zero-inflated negative binomial. Results were virtually identical across the four models, but the zero-inflated negative binomial had the best fit of the four models considered. Table 9 contains the Akaike Information Criteria (AIC) of the four models. Smaller values indicate better fit.

A zero-inflated negative binomial model was used to estimate the impact of unintentional opt-in on the consideration set, operationalized in this study as the number of colleges to which students sent scores. Predictors included an indicator of unintentional EOS opt-in, student covariates, census data, and the students' predicted probability of opting into EOS under the active choice policy. Inverse propensity score weights were used to balance group differences between unintentional opt-in and intentional opt-out samples. Results of the zero-inflated negative binomial model can be found in Table 10.

Results indicate that there was a significant effect of unintentional opt-in on both whether a student sent scores to any college and on the estimated number of colleges to which students sent scores. From the zeros model, the effect of unintentionally opting into EOS on sending test scores to zero colleges is $e^{-0.085}$—or an odds ratio of 0.919. This means that compared to intentional opt-outs, unintentional opt-ins had 8.1% lower odds of sending scores to zero colleges. By taking the inverse of this odds ratio, we can state more intuitively that unintentional opt-ins had odds of sending scores to at least one college that were 8.9% higher than the odds of intentional opt-outs. From the negative binomial model, the effect of unintentionally opting into EOS on the size of the college consideration set (among those who have non-null consideration

sets) is equivalent to an increase of $e^{0.0615}$–or a factor change of 0.063. This means that, conditional on sending scores to at least one college and holding all other factors constant, unintentional opt-ins had an estimated college consideration set that was 6.3% larger than the estimated college consideration set of intentional opt-outs.

Finally, we computed the estimated college consideration set size for *all* students in our sample by combining the information across the zeros and count models and holding all other variables in those models at their mean values. After doing this computation, we found that unintentionally opting into EOS increased the students' expected college consideration set size by 7.5%. Figure 3 shows the estimated size of the students' consideration set by ACT Composite score range for unintentional opt-ins and intentional opt-outs after assuming that all other characteristics of these two groups are the same. As seen in the figure, unintentional opt-ins sent their ACT scores to more colleges than their peers who intentionally opted-out. As also seen in the figure, regardless of the students' EOS opt-in status, higher-achieving students sent their test scores to a greater estimated number of colleges.

Discussion

This study investigated the impact of EOS opt-in on student outcomes by taking advantage of a change in ACT's EOS opt-in policy to create a group of supposed "unintentional opt-ins." These are students who had a low predicted probability of opting into EOS but nonetheless opted into EOS, presumably through inattention or carelessness. We defined this group by using the parameter estimates of a prediction model based on the behavior of students under an active choice policy to estimate student intention under a default opt-in policy. Inverse propensity score weighting was used to balance group differences between our unintentional opt-in and intentional opt-out samples.

We found that students who unintentionally opted into EOS were more likely to send scores to at least one college and more likely to send scores to greater numbers of colleges. These findings provide some evidence that student search services such as ACT's Enrollment Opportunity Service (EOS) are having the desired effect of increasing students' college consideration sets. This study expands upon previous research suggesting that overall, students who opt into search services tend to enroll in college at higher rates and are more likely to enroll at 4-year colleges (Moore, 2017). The ultimate goal for this line of research is to provide evidence that students benefit from search services, and to encourage students to take advantage of these services.

Limitations

After excluding students with a high predicted probability of opt-in, the analysis sample contained very few African American and Hispanic students, whereas White students were over-represented. However, since African American and Hispanic students have some of the highest EOS opt-in rates and had some of the lowest drops in EOS opt-in rates after the policy change, we believe that they were actually unlikely to opt in unintentionally. While we don't believe that this is a major flaw of the study, this element of our study design limits our ability to generalize the findings to African American and Hispanic students.

While we have a large set of covariates that we know to be related to EOS opt-in and score sending, we cannot capture all possible covariates. In particular, non-cognitive factors such as motivation and conscientiousness are likely predictors of college seeking behaviors, but these factors were not represented in the data available for this study. We did include the number of times tested, which can serve as a proxy for motivation, and we also include the students'

probability of opting into EOS under the active choice policy, as this may also serve as proxy for motivation.

Students in the analysis sample were much more likely to have missing self-reported data such as parent income and parent education than students in the overall ACT-tested population. Our belief is that students may have unintentionally opted into EOS because they were not taking the time to answer response-optional questions on the ACT registration form, which would include student demographics and the EOS opt-in. However, we were able to capture much of the missing parent income and education data at a local level by incorporating U.S. Census data.

Future Research

In addition to suggesting that other researchers attempt to replicate our findings, we believe that future research should also focus on the potential benefits of student search services in helping students to find a better-fitting college. For example, does opting into a search service expose students to more selective colleges that they may not have otherwise considered but for which they would be academically qualified? The impact of such services on longer-term outcomes such as college degree completion and workforce outcomes should also be explored.

An important contribution of this study to the literature is the methodology used, taking advantage of a policy change to create “unintentional opt-in” and “intentional opt-in” groups. In this case, we were able to use student data for which an unintentional opt-in was not possible to predict whether students had opted in unintentionally under a policy in which unintentional opt-in was possible. What this does not help us to answer, however, is whether participation in the search service has a benefit for students who intentionally opt into the service, such as African Americans or Hispanics who tend to opt into the service at very high rates. Exploring other

innovative research designs that would allow us to use observational data to test the causal effect of opting into the service on expanding college opportunity for these students is much needed.

In closing, student search services are meant to assist colleges in identifying potential students so that they can contact them and build a successful and diverse student body. These services are also intended to benefit students by exposing them to opportunities that they may not have been aware of, and this research provides some evidence that students may indeed benefit from their participation in these services by increasing their college consideration set. These types of services may be particularly beneficial to low-income, first-generation college students who may lack the social capital to find college resources on their own.

References

ACT. (2013). *College choice report part 1: Preferences and prospects. A profile of 2012 ACT-tested high school graduates.* Iowa City, IA: ACT.

ACT. (2014a). *College choice report part 3: Persistence and transfer. A profile of 2012 ACT-tested high school graduates.* Iowa City, IA: ACT.

ACT. (2014b). *Expanding opportunities: A college choice report for the graduating class of 2014 part 1: Preferences and prospects*. Iowa City, IA: ACT.

Bettinger, E. P., Long, B. T., Oreopoulos, P., & Sanbonmatsu, L. (2012). The role of application assistance and information in college decisions: Results from the H&R Block FAFSA experiment. *The Quarterly Journal of Economics, 127*(3), 1205-1242.

Hirano, K., & Imbens, G. W. (2001). Estimation of causal effects using propensity score weighting: An application to data on right heart catheterization. *Health Services & Outcomes Research Methodology, 2*(3), 259–278.

Ho, D. E., Imai, K., King, G., & Stuart, E. A. (2007). Matching as nonparametric preprocessing for reducing model dependence in parametric causal inference. *Political Analysis, 15*(3), 199-236.

Holland, P. W. (1986). Statistics and causal inference. *Journal of the American Statistical Association, 81*(396), 945–960.

Hossler, D., Kalsbeek, D. H., & Bontrager, B. (2015). Successful strategic enrollment management organizations. In D. Hossler, B. Bontrager, & associates (Eds.), *Handbook of Strategic Enrollment Management* (pp. 31-45). San Francisco, CA: Jossey-Bass.

Howell, J. S., Pender, M., & Kumar, A. (2016). Academic match and fit: What can we learn from stated preferences, student actions, and collegiate outcomes? In A. P. Kelly, J. S. Howell,

& C. Sattin-Bajaj (Eds.), *Matching Students to Opportunity: Expanding College Choice, Access, and Quality*. Cambridge, MA: Harvard Education Press.

Moore, J. M. (2017). *Do students who opt into ACT's Educational Opportunity Service (EOS) enroll in college at higher rates?* Iowa City, IA: ACT.

National Center for Education Statistics. (2017). *IPEDS: Integrated Postsecondary Education Data System.* Washington, D.C.: U.S. Department of Education, Institute of Education Sciences.

Plank, S. B., & Jordan, W. J. (2001). Effects of information, guidance, and actions on postsecondary destinations: A study of talent loss. *American Educational Research Journal, 38*(4), 947-979.

Ridgeway, G. (2006). Assessing the effect of race bias in post-traffic stop outcomes using propensity scores. *Journal of Quantitative Criminology, 22*(1), 1-29.

Rosenbaum, P. & Rubin, D. (1983). The central role of propensity score in observational studies for causal effects. *Biometrika, 70*(1), 41–55.

Ruffalo Noel Levitz (2016a). *2016 marketing and student recruitment practices benchmark report for four-year colleges and universities.* Cedar Rapids, IA: Ruffalo Noel Levitz. Retrieved from www.RuffaloNL.com/BenchmarkReports.

Ruffalo Noel Levitz (2016b). *2016 e-recruiting practices report for four-year and two-year institutions.* Cedar Rapids, IA: Ruffalo Noel Levitz. Retrieved from www.RuffaloNL.com/BenchmarkReports.

Thaler, R. H., & Sunstein, C. R. (2008). *Nudge: Improving Decisions about Health, Wealth, and Happiness*. New Haven, NJ: Yale University Press.

Table 1. Characteristics of Students Matched and Not Matched to Census Data

Variable	2014 Sample		2016 Sample	
	Not Matched	Matched	Not Matched	Matched
Sample Size	2,229	594,773	1,850	534,439
Mean ACT Composite	22.0	22.8	22.4	23.1
EOS Opt-In Rate	87%	89%	75%	74%
Parents No College	11%	13%	11%	13%
Parents Any College	68%	71%	66%	69%
Income < $36,000	23%	17%	20%	16%
Income > $100,000	16%	23%	16%	25%
African American	15%	9%	14%	9%
American Indian	1%	1%	1%	1%
Asian	6%	5%	9%	6%
Hispanic	17%	14%	18%	17%
Pacific Islander	0%	0%	0%	0%
White	48%	63%	45%	58%
Male	44%	45%	45%	45%
Reside in Midwest	11%	33%	9%	23%
Reside in Northeast	13%	14%	17%	18%
Reside in South	51%	37%	47%	39%
Reside in West	26%	16%	28%	19%

Table 2. Means, 2016 Data Sample (Active Choice Policy)

Variable	Opt-Ins		Opt-Outs	
	Mean	Standard Deviation	Mean	Standard Deviation
ACT Composite	22.6	5.3	24.5	5.4
ACT Composite Squared	538.0	248.3	626.6	262.1
Number of Times Tested	2.0	1.0	2.0	1.0
Female	0.57	0.50	0.52	0.50
Male	0.43	0.50	0.48	0.50
Parent Income < $36,000	0.19	0.39	0.07	0.26
Parent Income $36,000 - $60,000	0.14	0.35	0.07	0.26
Parent Income $60,000 - $100,000	0.18	0.38	0.12	0.33
Parent Income > $100,000	0.24	0.43	0.27	0.44
Parent Income Missing	0.26	0.44	0.47	0.50
Parent Education No College	0.15	0.35	0.06	0.24
Parent Education Some College	0.21	0.40	0.12	0.32
Parent Education Bachelor's	0.26	0.44	0.25	0.43
Parent Education Graduate Degree	0.24	0.43	0.28	0.45
Parent Education Missing	0.15	0.35	0.29	0.45
Degree Aspirations Less than Bachelor's	0.02	0.15	0.02	0.14
Degree Aspirations Bachelor's Degree	0.44	0.50	0.42	0.49
Degree Aspirations Graduate Degree	0.45	0.50	0.40	0.49
Degree Aspirations Missing	0.08	0.28	0.17	0.37
African American	0.10	0.30	0.04	0.20
American Indian	0.01	0.08	0.00	0.06
Asian	0.06	0.24	0.06	0.23
Hispanic	0.20	0.40	0.09	0.29
Pacific Islander	0.00	0.05	0.00	0.04
Two or More Races	0.04	0.20	0.03	0.17
White	0.54	0.50	0.71	0.46
Missing	0.05	0.21	0.07	0.25
Planned Major Agriculture	0.01	0.12	0.01	0.12
Planned Major Architecture	0.01	0.11	0.01	0.10
Planned Major Ethnic/Multidisciplinary Studies	0.00	0.03	0.00	0.03
Planned Major Arts	0.05	0.22	0.04	0.21
Planned Major Business	0.11	0.31	0.14	0.34
Planned Major Community/Family Services	0.02	0.12	0.01	0.10
Planned Major Communications	0.02	0.14	0.02	0.15
Planned Major Computer Science/Mathematics	0.03	0.18	0.04	0.19
Planned Major Education	0.04	0.20	0.04	0.19
Planned Major Engineering Tech/Drafting	0.01	0.11	0.01	0.09
Planned Major Engineering	0.10	0.30	0.09	0.29
Planned Major English/Foreign Language	0.01	0.11	0.01	0.11
Planned Major Health Admin	0.04	0.19	0.02	0.14

Planned Major Health Sciences	0.18	0.39	0.13	0.33
Planned Major Philosophy/Religion	0.00	0.06	0.00	0.06
Planned Major Repair/Construction	0.00	0.07	0.00	0.07
Planned Major Natural Sciences	0.09	0.28	0.08	0.28
Planned Major Social Sciences/Law	0.08	0.28	0.07	0.25
Planned Major Undecided	0.18	0.39	0.27	0.44
Planned Major Missing	0.00	0.03	0.00	0.03
Preferred College Type 4-Year Public	0.66	0.48	0.52	0.50
Preferred College Type 4-Year Private	0.19	0.39	0.23	0.42
Preferred College Type 2-Year	0.04	0.19	0.03	0.18
Preferred College Type Missing	0.11	0.32	0.22	0.42
Preferred College Out of State	0.22	0.41	0.23	0.42
Preferred College In State	0.64	0.48	0.48	0.50
Preferred College Missing	0.15	0.36	0.29	0.45
High School Type Public	0.81	0.40	0.71	0.46
High School Type Private	0.18	0.38	0.27	0.45
High School Type Missing	0.02	0.13	0.02	0.15
ACT Statewide Participation Rate	0.58	0.25	0.54	0.26
ACT Statewide Testing Indicator	0.13	0.34	0.12	0.33
Resides in Midwest	0.24	0.43	0.22	0.42
Resides in South	0.41	0.49	0.34	0.47
Resides in West	0.20	0.40	0.18	0.39
Resides in Northeast	0.16	0.36	0.25	0.44
Census Education Level Less Than High School	0.12	0.12	0.07	0.09
Census Education Level High School/GED	0.25	0.12	0.21	0.13
Census Education Level Some College	0.20	0.08	0.18	0.08
Census Education Level Associate's Degree	0.08	0.04	0.08	0.04
Census Education Level Bachelor's Degree	0.21	0.12	0.27	0.12
Census Education Level Master's Degree	0.10	0.08	0.13	0.09
Census Education Level Professional/Doctoral Degree	0.04	0.05	0.07	0.07
Census Income Level Less than $35,000	0.27	0.18	0.20	0.15
Census Income Level $35,000 - $60,000	0.19	0.09	0.16	0.09
Census Income Level $60,000 - $100,000	0.22	0.09	0.21	0.09
Census Income Level > $100,000	0.31	0.22	0.42	0.23

Table 3. Logistic Regression Results Predicting EOS Opt-in for 2016 Model under Active Choice Policy

Variable	Parameter Estimate	Standard Error	Odds Ratio
Intercept	-0.663	0.101	
ACT Composite	-0.029	0.005	0.971
ACT Composite Squared	0.000	0.000	1.000
Number of Times Tested	0.070	0.003	1.073
Female	0.085	0.007	1.089
Parent Income $36,000 - $60,000	-0.023	0.016	0.978
Parent Income $60,000 - $100,000	-0.066	0.015	0.936
Parent Income > $100,000	-0.300	0.014	0.741
Parent Income Missing	-0.662	0.014	0.516
Parent Education Some College	0.045	0.015	1.046
Parent Education Bachelor's	-0.082	0.015	0.921
Parent Education Graduate Degree	-0.093	0.016	0.912
Parent Education Missing	-0.435	0.017	0.647
Degree Aspirations Bachelor's Degree	0.340	0.026	1.405
Degree Aspirations Graduate Degree	0.602	0.027	1.826
Degree Aspirations Missing	0.179	0.029	1.196
African American	0.789	0.016	2.202
American Indian	0.485	0.053	1.624
Asian	0.405	0.015	1.500
Hispanic	0.715	0.012	2.043
Pacific Islander	0.474	0.074	1.607
Two or More Races	0.393	0.019	1.481
Missing	0.182	0.014	1.200
Planned Major Architecture	0.213	0.044	1.237
Planned Major Ethnic/Multidisciplinary Studies	0.117	0.102	1.124
Planned Major Arts	0.225	0.032	1.252
Planned Major Business	0.010	0.030	1.010
Planned Major Community/Family Services	0.138	0.042	1.148
Planned Major Communications	0.050	0.036	1.051
Planned Major Computer Science/Mathematics	0.154	0.033	1.167
Planned Major Education	0.132	0.033	1.141
Planned Major Engineering Tech/Drafting	0.310	0.044	1.363
Planned Major Engineering	0.248	0.030	1.281
Planned Major English/Foreign Language	0.191	0.042	1.210
Planned Major Health Admin	0.136	0.035	1.146
Planned Major Health Sciences	0.234	0.030	1.263
Planned Major Philosophy/Religion	0.075	0.063	1.078
Planned Major Repair/Construction	0.038	0.058	1.038
Planned Major Natural Sciences	0.171	0.031	1.187

Variable	Parameter Estimate	Standard Error	Odds Ratio
Planned Major Social Sciences/Law	0.201	0.031	1.223
Planned Major Undecided	-0.050	0.029	0.952
Planned Major Missing	0.417	0.108	1.518
Preferred College Type 4-Year Private	-0.040	0.009	0.961
Preferred College Type 2-Year	-0.185	0.021	0.831
Preferred College Type Missing	0.023	0.016	1.023
Preferred College In State	0.093	0.009	1.098
Preferred College Missing	0.056	0.014	1.058
High School Type Private	-0.297	0.009	0.743
High School Type Missing	-0.272	0.024	0.762
ACT Statewide Participation Rate	0.000	0.000	1.000
ACT Statewide Testing Indicator	0.142	0.015	1.153
Resides in Midwest	0.137	0.015	1.147
Resides in South	0.127	0.013	1.135
Resides in West	0.091	0.012	1.095
Census Education Level Less Than High School	2.356	0.085	10.544
Census Education Level High School/GED	1.460	0.078	4.308
Census Education Level Some College	1.831	0.083	6.242
Census Education Level Associate's Degree	1.555	0.101	4.735
Census Education Level Bachelor's Degree	1.103	0.084	3.013
Census Education Level Master's Degree	1.069	0.108	2.914
Census Income Level Less than $35,000	0.386	0.034	1.471
Census Income Level $35,000 - $60,000	0.372	0.045	1.451
Census Income Level $60,000 - $100,000	0.602	0.043	1.826

Table 4. Logistic Regression Results for 2014 Analysis Sample to Create IPWs

Variable	Parameter Estimate	Standard Error	Odds Ratio
Intercept	6.268	1.410	
ACT Composite	-0.170	0.033	0.843
ACT Composite Squared	0.002	0.000	1.002
Number of Times Tested	0.163	0.056	1.177
Female	0.151	0.069	1.163
Parent Income $36,000 - $60,000	-1.494	0.854	0.224
Parent Income $60,000 - $100,000	-0.612	0.721	0.543
Parent Income > $100,000	-1.377	0.688	0.252
Parent Income Missing	-2.283	0.828	0.102
Parent Education Some College	0.310	0.289	1.363
Parent Education Bachelor's	-0.008	0.259	0.992
Parent Education Graduate Degree	0.012	0.260	1.012
Parent Education Missing	-1.067	0.422	0.344
Degree Aspirations Bachelor's Degree	0.865	0.284	2.375
Degree Aspirations Graduate Degree	1.558	0.480	4.751
Degree Aspirations Missing	0.412	0.174	1.509
African American	2.449	0.755	11.574
American Indian	0.312	0.611	1.366
Asian	1.396	0.321	4.038
Hispanic	1.768	0.569	5.861
Pacific Islander	1.018	0.640	2.769
Two or More Races	0.972	0.320	2.643
Missing	0.267	0.145	1.305
Planned Major Architecture	0.548	0.238	1.729
Planned Major Ethnic/Multidisciplinary Studies	0.244	0.304	1.276
Planned Major Arts	0.364	0.218	1.439
Planned Major Business	-0.036	0.118	0.965
Planned Major Community/Family Services	0.067	0.218	1.070
Planned Major Communications	0.143	0.135	1.154
Planned Major Computer Science/Mathematics	0.048	0.178	1.049
Planned Major Education	0.199	0.169	1.221
Planned Major Engineering Tech/Drafting	0.428	0.345	1.535
Planned Major Engineering	0.595	0.228	1.813
Planned Major English/Foreign Language	0.279	0.208	1.322
Planned Major Health Admin	0.449	0.218	1.567
Planned Major Health Sciences	0.666	0.222	1.945
Planned Major Philosophy/Religion	0.039	0.231	1.040
Planned Major Repair/Construction	0.019	0.258	1.019
Planned Major Natural Sciences	0.358	0.181	1.430
Planned Major Social Sciences/Law	0.423	0.200	1.527

Variable	Parameter Estimate	Standard Error	Odds Ratio
Planned Major Undecided	-0.216	0.123	0.806
Planned Major Missing	0.793	0.424	2.209
Preferred College Type 4-Year Private	-0.151	0.048	0.859
Preferred College Type 2-Year	-0.663	0.184	0.515
Preferred College Type Missing	-0.179	0.042	0.836
Preferred College In State	0.281	0.084	1.324
Preferred College Missing	0.130	0.057	1.139
High School Type Private	-0.795	0.230	0.452
High School Type Missing	-1.045	0.222	0.352
ACT Statewide Participation Rate	0.004	0.001	1.004
ACT Statewide Testing Indicator	0.243	0.125	1.275
Resides in Midwest	0.266	0.117	1.305
Resides in South	0.268	0.104	1.307
Resides in West	0.193	0.078	1.213
Census Education Level Less Than High School	5.410	1.856	223.598
Census Education Level High School/GED	3.410	1.141	30.260
Census Education Level Some College	4.006	1.426	54.932
Census Education Level Associate's Degree	4.442	1.232	84.939
Census Education Level Bachelor's Degree	2.024	0.855	7.570
Census Education Level Master's Degree	1.662	0.846	5.272
Census Income Level Less than $35,000	1.051	0.327	2.859
Census Income Level $35,000 - $60,000	0.440	0.336	1.553
Census Income Level $60,000 - $100,000	1.585	0.488	4.879
Predicted Probability of EOS Opt In from 2016 Model	-8.255	3.345	0.000

Table 5. Unweighted and Weighted Means, 2014 Analysis Sample (Default Choice Policy)

Variable	Total (Weighted)	Opt-Ins	Opt-Outs (Weighted)	Opt-Outs (Unweighted)
ACT Composite	26.5	26.5	26.5	27.2
ACT Composite Squared	722.2	722.6	721.9	759.0
Number of Times Tested	1.8	1.8	1.8	1.8
Female	0.46	0.46	0.46	0.48
Male	0.54	0.54	0.54	0.52
Parent Income < $36,000	0.00	0.00	0.00	0.00
Parent Income $36,000 - $60,000	0.00	0.00	0.00	0.00
Parent Income $60,000 - $100,000	0.00	0.00	0.00	0.00
Parent Income > $100,000	0.05	0.05	0.05	0.04
Parent Income Missing	0.94	0.94	0.94	0.96
Parent Education No College	0.00	0.00	0.00	0.00
Parent Education Some College	0.01	0.01	0.01	0.00
Parent Education Bachelor's	0.11	0.11	0.11	0.08
Parent Education Graduate Degree	0.18	0.18	0.18	0.14
Parent Education Missing	0.70	0.70	0.70	0.78
Degree Aspirations Less than Bachelor's	0.02	0.02	0.02	0.01
Degree Aspirations Bachelor's Degree	0.32	0.32	0.32	0.26
Degree Aspirations Graduate Degree	0.25	0.24	0.25	0.21
Degree Aspirations Missing	0.41	0.42	0.41	0.51
African American	0.00	0.00	0.00	0.00
American Indian	0.00	0.00	0.00	0.00
Asian	0.03	0.03	0.03	0.03
Hispanic	0.01	0.01	0.01	0.01
Pacific Islander	0.00	0.00	0.00	0.00
Two or More Races	0.01	0.01	0.01	0.01
White	0.86	0.86	0.86	0.84
Missing	0.08	0.09	0.08	0.12
Planned Major Agriculture	0.01	0.01	0.01	0.01
Planned Major Architecture	0.01	0.01	0.01	0.01
Planned Major Ethnic/Multidisciplinary Studies	0.00	0.00	0.00	0.00
Planned Major Arts	0.03	0.03	0.03	0.03
Planned Major Business	0.18	0.18	0.18	0.17
Planned Major Community/Family Services	0.00	0.00	0.00	0.00
Planned Major Communications	0.03	0.03	0.03	0.03
Planned Major Computer Science/Mathematics	0.02	0.02	0.02	0.03
Planned Major Education	0.02	0.02	0.02	0.02
Planned Major Engineering Tech/Drafting	0.00	0.00	0.00	0.00
Planned Major Engineering	0.07	0.07	0.07	0.06
Planned Major English/Foreign Language	0.01	0.01	0.01	0.01

Variable	Total (Weighted)	Opt-Ins	Opt-Outs (Weighted)	Opt-Outs (Unweighted)
Planned Major Health Admin	0.01	0.01	0.01	0.00
Planned Major Health Sciences	0.05	0.05	0.05	0.04
Planned Major Philosophy/Religion	0.00	0.00	0.00	0.00
Planned Major Repair/Construction	0.00	0.00	0.00	0.00
Planned Major Natural Sciences	0.06	0.06	0.06	0.06
Planned Major Social Sciences/Law	0.04	0.04	0.04	0.04
Planned Major Undecided	0.44	0.44	0.44	0.46
Planned Major Missing	0.00	0.00	0.00	0.00
Preferred College Type 4-Year Public	0.23	0.23	0.23	0.16
Preferred College Type 4-Year Private	0.24	0.24	0.24	0.20
Preferred College Type 2-Year	0.01	0.01	0.01	0.01
Preferred College Type Missing	0.52	0.52	0.51	0.62
Preferred College Out of State	0.19	0.18	0.19	0.15
Preferred College In State	0.16	0.16	0.16	0.12
Preferred College Missing	0.65	0.65	0.65	0.74
High School Type Public	0.52	0.52	0.52	0.50
High School Type Private	0.46	0.46	0.46	0.47
High School Type Missing	0.02	0.02	0.02	0.03
ACT Statewide Participation Rate	0.43	0.43	0.43	0.41
ACT Statewide Testing Indicator	0.06	0.06	0.06	0.06
Resides in Midwest	0.17	0.17	0.17	0.15
Resides in South	0.26	0.26	0.26	0.26
Resides in West	0.16	0.16	0.16	0.17
Resides in Northeast	0.40	0.41	0.40	0.42
Census Education Level Less Than High School	0.03	0.03	0.03	0.03
Census Education Level High School/GED	0.12	0.12	0.12	0.12
Census Education Level Some College	0.13	0.13	0.13	0.13
Census Education Level Associate's Degree	0.06	0.06	0.06	0.06
Census Education Level Bachelor's Degree	0.34	0.34	0.34	0.34
Census Education Level Master's Degree	0.19	0.19	0.19	0.20
Census Education Level Professional/Doctoral Degree	0.12	0.12	0.12	0.13
Census Income Level Less than $35,000	0.12	0.12	0.12	0.12
Census Income Level $35,000 - $60,000	0.11	0.11	0.11	0.11
Census Income Level $60,000 - $100,000	0.17	0.17	0.17	0.16
Census Income Level > $100,000	0.60	0.60	0.60	0.61
Predicted Prob of EOS Opt In from 2016 Model	0.42	0.42	0.42	0.40

Table 6. Student Demographics in 2014 Data Samples (Default Choice Policy)

Variable	2014 ACT-Tested Graduates	2014 Cleaned Sample	2014 Analysis Sample
Sample Size	1,845,787	594,773	43,153
Mean ACT Composite	21.0	22.8	26.7
College Enrollment Rate	69%	82%	85%
EOS Opt In Rate	86%	89%	66%
Income < $36,000	24%	17%	0%
Income Missing	27%	29%	95%
African American	13%	9%	0%
American Indian	1%	1%	0%
Asian	4%	5%	3%
Hispanic	15%	14%	1%
Pacific Islander	0%	0%	0%
White	56%	63%	85%
Two or More Races	4%	3%	1%
Male	46%	44%	54%

Table 7. Race/Ethnicity and EOS Opt-In Rates of 2014 ACT-Tested Graduates and Analysis Sample

	2014 ACT-Tested Graduates		2014 Analysis Sample	
Race/ethnicity	Percent	Opt in Rate	Percent	Opt in Rate
African American	13.1	93	0.1	75
American Indian	0.8	87	0.0	44
Asian	4.4	89	3.1	71
Hispanic	15.2	91	0.7	64
Pacific Islander	0.3	86	0.0	63
White	56.3	85	85.4	67
Two or more races	3.8	89	1.1	64
Prefer not/no response	6.2	68	9.6	59

Table 8. EOS Opt-In Rates by Race/Ethnicity by ACT Test Year

Race/ethnicity	2013	2014	2015	2016
African American	95	95	89	87
American Indian	89	90	84	80
Asian	87	86	77	74
Hispanic	93	93	86	84
Pacific Islander	90	90	81	79
White	85	85	74	68
Two or more races	90	89	82	78
Prefer not/no response	59	61	54	51

Table 9. Akaike Information Criteria for Consideration Set Models Considered

Model	AIC
Poisson	346692.1
Negative Binomial	215161.0
Zero-Inflated Poisson	277993.6
Zero-Inflated Negative Binomial	198045.5

Table 10. Zero-Inflated Negative Binomial Regression Results Predicting Number of Scores Sent

Variable	Parameter Estimate	Standard Error of Parameter Estimate	Zero Inflation Parameter Estimate	Standard Error of Zero Inflation Parameter Estimate
Intercept	3.0356	0.5192	0.797	2.038
EOS Opt-In	0.0615	0.0075	-0.085	0.033
ACT Composite	-0.0642	0.0133	0.431	0.050
ACT Composite Squared	0.0017	0.0002	-0.014	0.001
Number of Times Tested	0.2379	0.0211	-2.051	0.090
Female	0.1353	0.0261	-0.028	0.104
Parent Income $36,000 - $60,000	0.2281	0.3	0.015	1.096
Parent Income $60,000 - $100,000	0.384	0.2279	0.316	0.862
Parent Income > $100,000	-0.0472	0.2219	-0.042	0.852
Parent Income Missing	-0.4661	0.2829	-0.033	1.100
Parent Education Some College	0.134	0.1095	0.167	0.386
Parent Education Bachelor's	-0.1225	0.1001	0.068	0.351
Parent Education Graduate Degree	-0.1218	0.1007	0.144	0.354
Parent Education Missing	-0.5506	0.1618	0.026	0.613
Degree Aspirations Bachelor's Degree	0.4835	0.1089	-0.260	0.426
Degree Aspirations Graduate Degree	0.8457	0.1834	0.373	0.722
Degree Aspirations Missing	0.2889	0.0676	0.004	0.259
African American	0.9141	0.2801	0.982	1.067
American Indian	0.9979	0.242	0.521	0.830
Asian	0.6426	0.1216	1.213	0.483
Hispanic	0.9417	0.2166	0.689	0.857
Pacific Islander	0.3287	0.2464	-0.747	0.945
Two or More Races	0.4605	0.1206	-0.083	0.486
Missing	0.272	0.0552	0.430	0.219
Planned Major Architecture	0.3594	0.0874	0.875	0.354
Planned Major Ethnic/Multidisciplinary Studies	0.141	0.1088	0.876	0.478
Planned Major Arts	0.3462	0.0815	0.608	0.330
Planned Major Business	0.0544	0.0422	0.557	0.180
Planned Major Community/Family Services	0.0581	0.0833	0.169	0.331
Planned Major Communications	0.2143	0.0478	0.447	0.204
Planned Major Computer Science/Mathematics	0.2249	0.0654	0.624	0.271
Planned Major Education	0.1742	0.0622	0.261	0.255

Variable	Parameter Estimate	Standard Error of Parameter Estimate	Zero Inflation Parameter Estimate	Standard Error of Zero Inflation Parameter Estimate
Planned Major Engineering Tech/Drafting	0.3636	0.1307	0.508	0.515
Planned Major Engineering	0.3345	0.0849	0.845	0.346
Planned Major English/Foreign Language	0.3	0.0772	0.997	0.314
Planned Major Health Admin	0.1785	0.0795	0.323	0.321
Planned Major Health Sciences	0.3217	0.0824	0.623	0.336
Planned Major Philosophy/Religion	0.0228	0.0871	0.232	0.358
Planned Major Repair/Construction	-0.0834	0.1201	0.271	0.368
Planned Major Natural Sciences	0.2635	0.0666	0.855	0.275
Planned Major Social Sciences/Law	0.3278	0.0742	0.762	0.304
Planned Major Undecided	-0.0032	0.0441	0.723	0.186
Planned Major Missing	0.6648	0.1614	0.516	0.625
Preferred College Type 4-Year Private	-0.0493	0.017	0.363	0.072
Preferred College Type 2-Year	-0.4396	0.0762	0.053	0.274
Preferred College Type Missing	0.0297	0.0148	0.063	0.064
Preferred College In State	0.0146	0.0311	-0.282	0.127
Preferred College Missing	0.0555	0.0206	0.299	0.086
High School Type Private	-0.3191	0.0878	0.323	0.348
High School Type Missing	-0.6085	0.0863	0.257	0.338
ACT Statewide Participation Rate	-0.0036	0.0003	0.001	0.001
ACT Statewide Testing Indicator	0.3261	0.0467	-0.121	0.199
Resides in Midwest	0.0201	0.0441	-1.235	0.182
Resides in South	-0.0084	0.0393	-0.685	0.156
Resides in West	0.1688	0.0291	-0.558	0.117
Census Education Level Less Than High School	2.8578	0.7077	0.819	2.796
Census Education Level High School/GED	1.2767	0.436	-0.276	1.721
Census Education Level Some College	1.5664	0.5443	-1.434	2.152
Census Education Level Associate's Degree	1.3083	0.4704	-0.676	1.856
Census Education Level Bachelor's Degree	1.0255	0.3271	-0.302	1.291
Census Education Level Master's Degree	1.0136	0.3225	-0.064	1.277
Census Income Level Less than $35,000	0.4341	0.1236	0.451	0.494
Census Income Level $35,000 - $60,000	0.1438	0.1265	0.433	0.505

Variable	Parameter Estimate	Standard Error of Parameter Estimate	Zero Inflation Parameter Estimate	Standard Error of Zero Inflation Parameter Estimate
Census Income Level $60,000 - $100,000	0.4179	0.185	-0.359	0.737
Predicted Probability of EOS Opt In from 2016 Model	-5.0713	1.2692	-2.652	5.047
Dispersion	0.2873	0.0047		

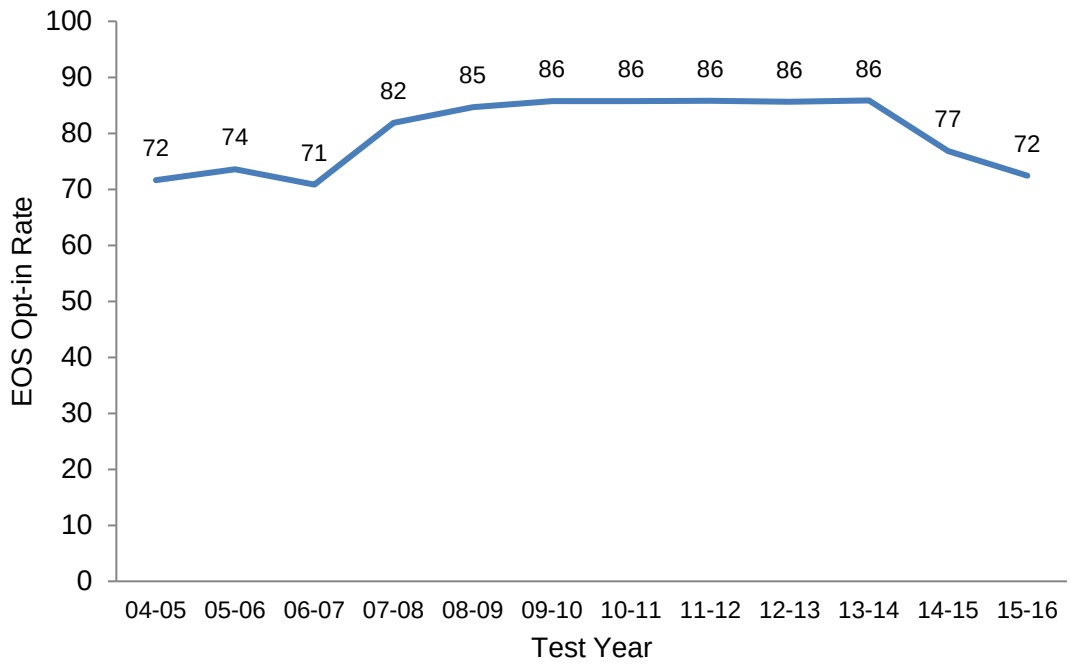

Figure 1. EOS Opt-in Rates by Test Year (National Test Dates Only).

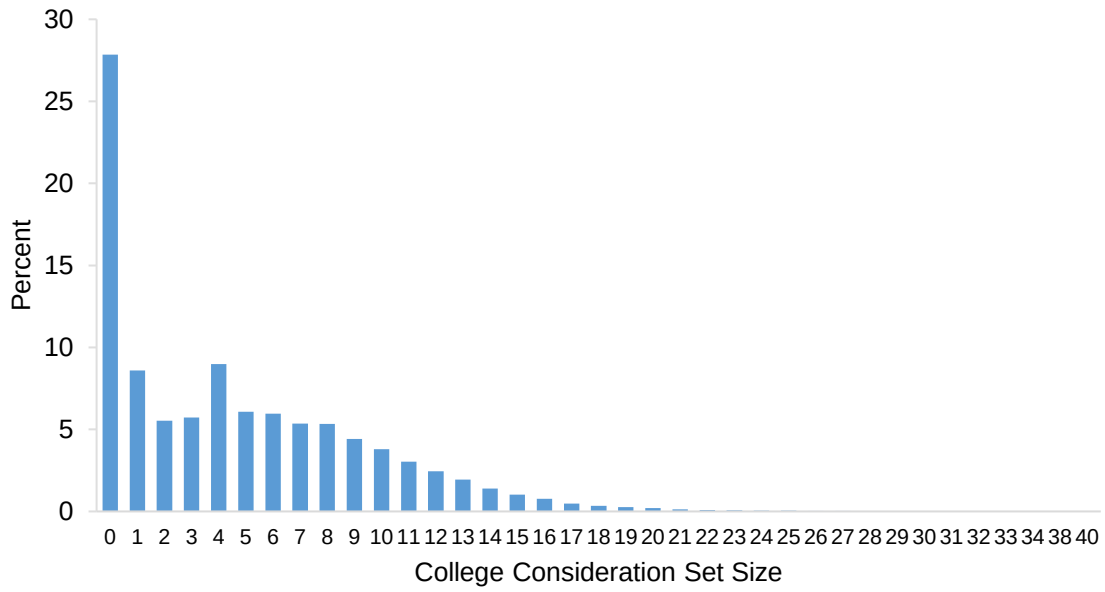

Figure 2. Distribution of College Consideration Set Sizes.

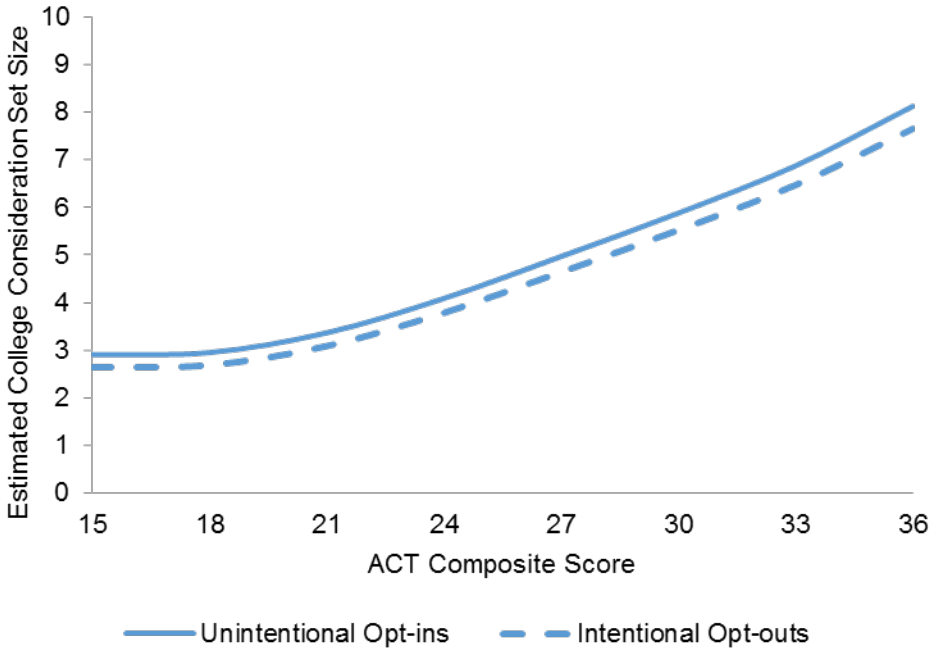

Figure 3. Estimated Size of Students' College Consideration Set