The Bottom Line on College Counseling*

Andrew Barr[†] & Benjamin Castleman[‡]

October 2017

Abstract

Low-income students are substantially less likely to graduate from college than their high-income peers. In response to this disparity, federal and state governments and local communities have invested heavily in college advising programs as a strategy to support low-income and first-generation students during the college process. Despite the volume of programs and magnitude of financial investment, rigorous evidence of their impact on student college success is limited. Our paper contributes new, precisely estimated evidence of the effects of an intensive college advising program. We conducted a multi-cohort randomized control trial of the Bottom Line (BL) college advising model. We find that the BL model of advising students during high school and into college, combined with explicit guidance to students about applying to and attending institutions where they are likely to be successful without incurring substantial costs, leads to large effects on college enrollment and four-year college enrollment. In contrast to most interventions, these effects grow over time as program participants are substantially more likely to persist in college than control students who did not receive BL advising. Additional results using survey data, detailed counselor-student interaction data, and quasi-random counselor assignment indicate that the program has little effect on FAFSA filing, but instead works by altering application behavior, helping students balance cost and quality considerations in choosing where to enroll, and providing ongoing support while students are in college. Program effects are remarkably consistent across space, time, counselors, and student characteristics, suggesting that the BL model is highly scalable. Back of the envelope calculations suggest that if the BL model were adopted broadly it would cut the income gap in four-year college enrollment in half.

*We are grateful to Bottom Line for partnering with us on designing an experimental evaluation of their program. We are grateful for financial support from the Michael & Susan Dell Foundation, the Coalition for Evidence-Based Policy, and the Laura and John Arnold Foundation. We thank seminar participants at the 2017 CESifo Economics of Education meeting.

[†]Department of Economics, Texas A&M University, abarr@tamu.edu

[‡]Curry School of Education and Batten School of Public Policy, University of Virginia, castleman@virginia.edu

1 Introduction

The economic returns to postsecondary education continue to widen over time, with growing evidence that attending higher-quality institutions increases the probability that students complete college and realize a greater return on their degree (Hoekstra, 2009; Goodman, Smith, and Hurwitz, 2016; Hoxby and Turner, 2013; Zimmerman, 2014). At the same time, socioeconomic gaps in college completion have widened; disparities in college success by family income persist even upon control for academic achievement (Bailey and Dynarski, 2011; Belley and Lochner, 2007).

In response to this disparity, federal and state governments and many communities have invested in intensive college advising programs as a strategy to help low-income and first-generation students apply to well-matched institutions and complete financial aid applications. These initiatives are widespread — the National College Advising Network estimates its member organizations serve two million students per year — and have received national attention and support as a promising approach to expand college opportunity for low-income and first-generation students (e.g. Executive Office of the President, 2014). These initiatives have garnered hundreds of millions of dollars in public and private investment, on top of the billion dollars spent on traditional high-school counselors.

Yet despite the volume of programs and the magnitude of financial investment in these organizations, rigorous evidence of their impact on students' college success is fairly limited. Our paper contributes new, precisely-identified evidence of intensive college advising on students' college access and persistence. We conducted a multi-cohort, randomized controlled trial of the Bottom Line (BL) college advising program, which operates in several cities in Massachusetts, New York, and Illinois. Bottom Line is also in the process of exploring scaling to additional states.[1] BL counselors provide individualized advising to students from the summer before senior year of high school through the summer after high school. Counselors work with students on identifying well-matched colleges to apply to and on completing and

[1]BL's site in Chicago opened in 2014 and is not included in our analysis.

submitting college applications. BL also places particular emphasis on supporting students with their financial aid applications and on helping students evaluate the affordability of different postsecondary options through intensive analysis of students' financial aid packages and colleges' full cost of attendance.

A unique component of the BL model is that counselors encourage students to apply to and attend a set of target colleges and universities that BL has identified as providing students with an optimal combination of quality and affordability. Notably, many of the institutions BL encourages students to attend resemble the high-mobility, mid-tier public institutions described in Chetty et al.'s (2017) analysis. For students who enroll at one of the target institutions (approximately 50 percent of advisees choose to do so), BL continues to provide individualized, campus-based support to students for up to six years following high school.

To preview our results, we find that students randomly offered BL advising are substantially more likely to enroll and persist in college than students who applied to receive BL but who were not offered advising. Pooling across cohorts (high school graduating classes of 2015 and 2016), students offered BL were 7 percentage points likely to enroll in college, relative to a control group enrollment rate of 83 percent. While these overall enrollment effects are quite large relative to most rigorous estimates of the effects of pure counseling programs, the focus of the BL model is promoting four-year college enrollment and completion. We find even larger effects on four-year enrollment, with a consistent 10 percentage point increase across cohorts; this is a 15 percent increase relative to four-year enrollment in the control group. In contrast to nearly all other interventions, in which intervention effects fade over time, the effects of BL are 40 percent larger in the 2nd year after high school graduation, during which treated students are 14 percentage points more likely to be enrolled in a four-year college than their control group counterparts. Additional evidence suggests that this is largely due to the continued counseling presence during college.[2] Similarly, students offered advising

[2]For instance, our results indicate that BL's continuing counseling presence plays an important role, with treated students at BL target schools 6.8 percentage points more likely to persist into the second year than

are 10 percentage points more likely to remain continuously enrolled in college over the first three semesters following high-school graduation. While students with low high-school GPAs appear to benefit somewhat more from access to BL counselors, the effects are surprisingly consistent across other types of students and across the two cohorts.

In the second half of the paper we examine (1) why the BL model is effective, and (2) what aspects of the BL model contribute to effects persisting over time. Detailed counselor-student interaction data indicate that the counselors appear to play a particularly important role in shaping school choice. Counselors moreover invest substantial time working with students to interpret financial aid letters and to choose affordable institutions.[3] The effects of these interactions around school choice and affordability are born out in survey data. While treated and control students were equally likely to apply to college and for financial aid, treatment students applied to significantly more colleges. Furthermore, they were much more likely to discuss their financial aid award letter with someone and to consider costs in their decisions about where to enroll.

A significant question about our findings is whether the BL model is likely to be scalable to different contexts and populations. For example, BL may be harder to scale if there is significant heterogeneity in the effectiveness of individual counselors. To investigate this particular question, we also leverage the quasi-random assignment of counselors to investigate how counselor advising behavior, as well as counselor backgrounds and characteristics, affect student outcomes. We find little relationship between counselor demographics and counselor effectiveness. Indeed, when we estimate counselor fixed effects, 29 out of the 30 counselors have a positive effect on four-year college enrollment. This lack of heterogeneity across different types of counselors supports the potential for broad scalability of BL.

Our results build on prior experimental studies of college advising programs in several important ways. Ours is the first evaluation of which we are aware that rigorously investigates an advising program that provides intensive advising during both high school and throughout

those in the control group at the same colleges.

[3]In contrast, there is no effect on the likelihood of filing a FAFSA.

college (for many BL students), and ours is the first paper of which we are aware that finds substantial increases in continuous enrollment for the overall sample that grow over time. This contrasts with much of the literature, which either uses a non-experimental design (Castleman and Goodman, 2016; Constantine et al 2006; Stephan and Rosenbaum, 2013)[4], provides imprecise estimates (Avery 2010, Avery 2014), finds no impact (Seftor, Mamun, and Shirn, 2009), finds impacts that are driven by particular sub-groups, or has effects that fade over time (Carrell and Sacerdote 2017; Avery 2013; Bos et al. 2012). Second, our study is able to identify the impact of intensive counseling separate from financial support for students such as application fee waivers that are simultaneously given in other programs (e.g. Carrell and Sacerdote, 2017). Given evidence that even very small differences in costs can affect students' engagement in college planning (Pallais, 2015), it is important to separate the impact of advising from the impact of relaxing financial constraints. Third, our survey results, detailed counselor-student interaction data, and quasi-random counselor assignment indicate that the program has little effect on FAFSA filing, but instead works by altering application behavior, helping students balance cost and quality considerations in choosing where to enroll, and providing ongoing support while students are in college. Finally, the consistency of our results across space, time, counselors, and students indicate that the BL model provides a scalable solution to closing the income gap in college enrollment and success.[5] Back of the envelope calculations suggest that if the BL model were adopted broadly it would cut the income gap in four-year college enrollment in half.[6]

[4]Several studies exploit natural variation in program availability and take up, finding mixed, but mostly positive, effects on enrollment outcomes (Castleman and Goodman, 2016; Constantine et al 2006; Stephan and Rosenbaum, 2013). Because of their identification strategies, however, these studies either lack precision, provide estimates local to a narrow margin of potentially college-going students, or face difficulty in isolating the unique impact of these interventions on students' college outcomes. For example, Castleman and Goodman's estimates rely on a manipulable running variable (GPA), are relevant only to students' around the 2.5 GPA threshold, and include a 95 percent confidence interval on the effect on 4-year enrollment that includes effects as small as *negative* 20 percentage points and as large as 40 percentage points. Constantine et al. 2006 use propensity-score matching, noting that " propensity score methods specifically, do not replicate findings from randomized studies well."

[5]Indeed, the New York City program only began with the high-school graduating class of 2012 and thus provides a more direct test of the scalability of the program. We find similarly large effects of the program there.

[6]Based on a comparison of the college enrollment rates of high-school graduates with GPAs over 2.5

2 Background

BL began in Boston in 1997 and now operates programs in Boston, Worcester, MA, New York City, and Chicago. Students are initially admitted into the Access program, which provides students with college and financial aid application support during high school. BL actively promotes the Access program through high schools and non-profit partners in each community and students apply to the Access program during the second half of their junior year of high school. BL collects a substantial amount of self-reported academic and demographic information from students through the application, and verifies self-reported family income and academic performance information through tax records and high school transcripts, respectively. Students are eligible for BL if their families make less than 200 percent of the federal poverty guidelines and if they have a high school GPA of 2.5 or higher.

BL counselors begin working with admitted students between the end of their junior year and the start of their senior year of high school. Advisors work full time. All counselors have a college degree and 17 percent have a masters degree. Most counselors are female (75 percent) with roughly a quarter black and a quarter Hispanic. The median counselor age is 26. Advisors have an average caseload of 40-60 students and meet with each student for an hour every three or four weeks during senior year, at BL's office in each community. BL counselors provide comprehensive college and financial aid support for students, ranging from creating lists of potential schools, writing essays and completing applications, to applying for financial aid, searching for scholarships, interpreting financial aid award letters, and selecting a college or university that aligns with students' goals and circumstances. BL advising places particular focus on college choice and affordability. Advisors work with students to understand the net price of colleges they are considering applying to, to complete the Free Application for Federal Student Aid (FAFSA) and supplementary financial aid forms (if required) in advance of priority deadlines, and to make fully-informed decisions about the

from families above and below 185 percent of the poverty line (authors' calculations using the High School Longitudinal Study of 2009 (HSLS: 09)).

affordability of each college to which they have been admitted based on a thorough understanding of both financial aid award letters and the cost of attendance at each institution. We provide descriptive statistics on the frequency and trends in counselor engagement with students, and the topics counselors and students discuss, in the "Exploring Access Counselor Effectiveness" section below.

Once students have chosen where to enroll in college, students who plan to attend one of BL's target institutions are invited to continue into the Success program.[7] Through the Success program, BL first provides ongoing advising during the summer after high school to help students navigate and complete required pre-matriculation tasks such as attending orientation, completing placement tests, or setting up a tuition payment plan. Campus-based counselors at each target institution than continue to meet regularly with students once they have matriculated in college; first-year students meet with counselors approximately three to four times per semester, while older students meet with a counselor twice a semester on average. Counselors provide a combination of academic support (e.g. course selection and making use of advising and tutoring services), social support (e.g. helping students adjust to a new environment, getting involved with activities and student groups), and advise students on how to balance academic, work, social, and family commitments. We provide summary statistics on the subjects (introduction, financial aid, application) and methods (in-person, phone, etc.) of counselor engagement below.

3 Experimental Design

We collaborated with BL staff to modify its student application processes in the spring of 2014 and spring of 2015 to incorporate a lottery design into BL's selection of applicants. In the spring of 2014 BL accepted applications in two waves: one application window closed at the end of May and the other application window closed at the end of August 2014, and in

[7] Appendix Table A1 shows the list of encouraged institutions at each BL site

2015 BL accepted applications in one wave, at the end of August 2015. Students provide a variety of demographic, academic, and family financial information on the application (see additional detail on data elements contained in the application below). Among students who meet the BL eligibility criteria (GPA of at least 2.5, family income below 200 percent of the poverty line, students being the first in their family to go to college), we randomized students to either receive an offer to participate in the BL Access advising program or to be in a control group that did not receive any BL services. In each site BL had minimum commitments to its funders and community partners of the number of students it had to serve, which are reflected in the treatment/control ratios we report in Table A2.

3.1 Data

Our data come from four primary sources: the BL application, BL counselor interaction data, two surveys we conducted with students during the spring of their senior year in high school and the fall after high school graduation, and the National Student Clearinghouse, from which we obtained college enrollment data. The BL application collects rich student-level baseline information, including race/ethnicity, gender, whether the student is the first in their family to go to college, whether they were working with another college access organization at the time they applied for BL, their high school GPA and SAT/ACT scores (if they had taken the exam), family income, and whether they had a sibling who had participated in BL. The interaction data contains detailed information on each interaction students had with a counselor, including the topic discussed, assistance the counselor provided with this topic, and narrative comments from the counselor about their interaction with students. Our spring of senior year survey asked students where applied to college and whether they had been accepted to each institution; whether and when students applied for financial aid; whether students received assistance reviewing their financial aid award letters, as well as a series of questions about factors influencing students' decisions about whether and where to enroll in college. Our fall after high school survey asked about students' enrollment intensity, campus engagement, course taking, and employment. The National Student Clearinghouse (NSC) provides student*term-level college enrollment data, with coverage across 96 percent of college enrollments in the country. NSC reporting is particularly high in Massachusetts and New York, where most BL students enrolled in college (Dynarski, Hemelt, and Hyman, 2015).

3.2 Baseline Equivalence

In Table 1, we report results from models in which we regress student-level baseline characteristics on the treatment indicator and site*cohort fixed effects. Across 20 baseline measures we only find 2 statistically significant difference between the treatment and control group at the 10 percent level, which is probabilistically what we would expect given the number of tests we conduct.

4 Empirical Strategy and Results

We estimate the effects of an offer to participate in BL on a variety of college preparation behaviors as well as on college enrollment, enrollment quality, and persistence in college. As the proportion assigned to treatment varied by site and cohort, we follow the usual approach in controlling for site by cohort fixed effects. In most specifications we condition on covariates to increase precision. Our basic specification is:

$$y_i = \alpha + \beta X_i + \theta Treatment_i + \sum_j \gamma_j l_{ij} + \varepsilon_i \tag{1}$$

where y_i is generally an enrollment outcome for individual i and X_i includes baseline demographic controls (gender, race, citizenship), measures of family resources and background (parents' AGI, parental employment status, household size, first generation status, whether sibling went to college), measures of aptitude (standardized GPA, state standardized test scores), and measures of college guidance resources (whether student is working with another counseling organization, whether sibling participated in BL). The l_{ij} are site by cohort fixed effects. These are included because the probability of being assigned to treatment varies by site and cohort. The coefficient of interest is θ, which is the intention to treat (ITT) estimate.

4.1 Enrollment

Table 3 contains our baseline estimates. We present results for the full sample as well as separately for the 2014 (Cohort 1) and 2015 (Cohort 2) high school graduating classes. The point estimate in the first row of column (2) shows that assignment to treatment increases the likelihood of college enrollment by 7 percentage points. This effect appears to be similar across both cohorts (columns (4) and (6)). While these overall enrollment effects are quite large relative to most rigorous estimates of the effects of pure counseling programs, the focus of the BL model is promoting four-year college enrollment. Estimates in the second row of Table 3 indicate even larger effects on four-year enrollment, with a consistent 10 percentage point increase across cohorts; this is a 15 percent increase relative to four-year enrollment in the control group. As expected, estimates in the third row indicate a reduction in two-year enrollment contributed to the rise in four-year enrollment.

Estimated treatment effects are somewhat larger for Hispanics and individuals with lower high school GPAs, with increases in college enrollment of 8 and 10 percentage points, respectively. These larger enrollment effects appear to be driven primarily by increases in four-year enrollment, with both groups 12-13 percentage points more likely to enroll in a four-year college. With these exceptions, our estimates of the effects of counseling are generally quite similar across subgroups (Table 4). There is no statistical difference in the estimated effect of the program when comparing men versus women, black versus white students, or students from families with higher or lower income levels. Similarly, participation in an alternative counseling program does not appear to attenuate the effects of the BL treatment. In summary, the counseling intervention appears to produce large increases in college enrollment and four-year college enrollment that are consistent across cohorts and types of students. These effects are even more striking when one considers that 44 percent of the sample participated in an alternative counseling program, so were already getting some form of college and/or financial aid advising at the same time that they were engaged with BL. This suggests that BL's particular approach to college counseling generated substantial value add for students. We explore potential mechanisms driving the "BL effect" below.

4.2 Persistence

While college enrollment has increased dramatically over the last thirty years, the rate of four year college completion has barely increased. Most of these marginal students fail to make it past the first year. Similarly, many interventions (counseling and otherwise) find effects on initial enrollment that tend to fade or even completely disappear over time. One of the distinguishing features of the BL model is continued support of students both during the college transition and while in college. An important and open question is whether this ongoing support in turn leads to sustained positive impacts on students' college success, or whether the observed effects of treatment fade, as is the case in nearly all other interventions. Table 5 presents effects of treatment on various measures of persistence for Cohort 1. The effects of treatment are even larger in the 2nd year after high school graduation than they are after the 1st. The offer of BL advising results in an 8 percentage point increase in the likelihood of being enrolled and a 14 percentage point increase in the likelihood of being enrolled in a four-year college. These effects are roughly 40 percent larger than the effects observed one year prior. Rows 4 and 5 similarly suggest that treatment has resulted in large increases in persistence. Treated students have enrolled for 0.2 more total semesters and were roughly 10 percentage points more likely to have been continuously enrolled during the three semesters following high-school graduation.

Table 6 shows how these effects vary across subgroups. Again, there appears to be a somewhat larger effect of counseling for individuals with lower GPAs, suggesting that counseling may be particularly beneficial for marginal students. With this slight exception, the effects are quite similar across subgroups, with large increases in 2nd year enrollment and measures of attainment for all types of individuals.

5 Mechanism

The size and persistence of effects leads to a natural question: why is this model of college counseling so effective when so many other models produce limited or no enrollment effect, effects only for certain subgroups, or initial effects on college enrollment that fade or disappear entirely over time? In this section, we attempt to more rigorously measure what counselors do and what appears to work, leveraging survey data, rich student-counselor interaction data, and the quasi-random assignment of students to counselors. Finally, we attempt to disentangle potential explanations for the BL model's effectiveness in helping students persist in college.

5.1 Exploring Access Counselor Effectiveness

BL maintains detailed data on counselor-student interactions. Counselors record a note detailing the date, mode of contact, and purpose of each interaction. They also enter a written summary of the substance of the meeting. Table 2 contains summary statistics generated from these data for the period between the beginning of the Access counseling program (May of student's Junior year of high school) and the transition period to college (August after a student's Senior year of high school). As seen in the table, nearly every student assigned to treatment (97 percent) had at least one interaction with a counselor during this period. While nearly every student (95 percent) had an in-office meeting with a counselor, only a third talked to a counselor on the phone. Over the 15 month period, counselors interacted with students an average of 13 times, with the majority of these interactions occurring as in-person meetings in the counselor's office.

Figure 1 illustrates the fraction of student-counselor interactions by months since the beginning of the counseling program. As the BL model begins at the end of a student's junior year of high school, month 0 is set to equal May of 2014 for the high school class of 2015 and May of 2015 for the high school class of 2016. As illustrated in the figure, counselors begin interacting with students in the summer after their junior year and continued interacting with most students at high levels into the spring of the following year. The level of interaction dips somewhat following high school graduation, and rises slightly again as students' transition into college. During the summer period, the students who have chosen to attend a BL target college were transitioned to the BL Success program and matched with a different BL counselor assigned to their particular school.

In addition to illustrating the high and persistent level of student-counselor interaction, the interaction data provide a way to quantify what counselors are spending time on during these meetings. The bottom third of Table 2 indicates that most meetings involve working on applications (3.47 meetings per student) or financial aid (2.03 meetings per student).

Students also have one to two more general introductory meetings ("first meetings") that tend to occur during the summer between their Junior and Senior year. During these meetings, counselors talk informally to students about their background, their college preferences, what they are most concerned about, and how they can help them. Counselors also take somewhat standardized notes during these meetings, indicating whether students are on time or exhibiting any odd behaviors in addition to providing a summary of the substance of the discussion. During this or the next meeting, counselors will work with students to develop a target school list based on student standardized test scores, GPAs, and preferences. In general, counselors try to guide students to choose schools with relatively low costs and high graduation rates. The set of schools that possess these traits tend to coincide with the set of target colleges where BL has a continued counseling presence.

In the fall of their Senior year, students have one or two additional meetings ("second meetings") to discuss their college list and potentially receive additional help with their essays. Based on information from BL on average meeting durations, we estimate that counselors spend an average of 10 to 15 hours working directly with each student between the summer after their Junior year and the summer after their Senior year.

Whereas the administrative data provide a good indication of how counselors spend their time helping students, they provide relatively little indication of the specific changes in students' actions, behaviors, and/or attitudes that led to the pronounced impacts we observe on college enrollment and persistence. To better understand the channels through which the BL counseling may have affected students' college decisions and outcomes, we turn to survey data.

We conducted a survey of both treatment and control group students in the first cohort during their spring of the senior year of high school (2015). We asked about students' college and financial aid application decisions and behaviors; where they had been accepted as of the time of the survey; and the sources of advising and support students relied on when making college and financial aid decisions (for treatment group students, this included questions about their BL counselor). Approximately 60 percent of students responded to the survey, with roughly equal response rates among treatment and control group students.

One interesting finding that emerges is that nearly all survey respondents in the control group —those who applied for BL but were not selected to participate — applied to college and for financial aid, even in the absence of BL advising. This suggests that control group students were able to access college planning guidance and support from other sources, or had sufficient motivation and college aspirations to complete these tasks independently. Students in both groups also applied to a large volume of colleges and universities — 10 on average for control group students and 13 on average for students in the treatment group. Both treatment and control group students appear to evaluate potential college choices similarly. For instance, both groups ranked overall costs and academic quality highly, while athletic programs were less important.

While both groups applied to college at very high rates, students in the treatment group were 10 percent more likely to rank costs as one of the top two factors in deciding where to attend. They were also more confident that they would be able to afford college, potentially a result of their much higher (20 percentage points) likelihood of meeting with someone to review their financial aid award letters.

In terms of students' responses about sources of college and financial aid advising, treatment students rate BL advising as the most important source of guidance; 58 percent of treatment students indicated that BL advising was "very important" in their application and decision process. In contrast, only 21 percent of control group students indicated that "staff at other college access programs" were very important. Both groups ranked support from parents (60 percent), counselors (50 percent), and teachers (30 percent) as very important.

Interestingly, among students who ranked parents, counselors, or teachers as important, treatment students were less likely to say they discussed college-related issues (e.g., which colleges to apply to or how to apply for financial aid) with these other adults. This suggests treatment students were receiving more guidance on these topics from BL counselors, and perhaps felt less need to turn to other (and potentially less-informed) sources of advising for this information.

5.2 Do Effects Vary across Counselors?

One question related to mechanism is whether the large observed treatment effects on enrollment and persistence vary across counselors. Understanding the extent to which effects vary across counselor characteristics/behavior will provide insight into the channels through which BL is influencing behavior as well as the extent to which the BL model can be scaled.[8]

[8] If only counselors with certain characteristics/behaviors are effective and counselors with these characteristics are in short supply, it would be more difficult to scale the program.

Figure 2 plots estimates of counselor fixed effects on college enrollment and four-year college enrollment. As seen in the Figure 2, 27 out of 30 counselors have a positive fixed effect on college enrollment. Even more impressive, 29 out of 30 counselors have a positive fixed effect on BL's focal outcome, four-year enrollment. This is further compelling evidence of the scalability of the BL model.

Of course, the preponderance of positive counselor fixed effects may reflect some sorting of students who need the most help to the most effective counselors. The inclusion of baseline covariates, suggests that this is not the case. After controlling for a rich set of student baseline covariates, 28 out of 30 counselors have a positive fixed effect on college enrollment and 29 out of 30 have a positive effect on four-year enrollment.

Despite the suggestion of positive impacts across nearly all counselors, these figures do not necessarily indicate the causal effect of particular counselor characteristics on student outcomes. Counselors in high schools and other college access organizations often have some say in where or who they counsel. Counselor preferences (and thus characteristics) could therefore be correlated with the ability, family background, and motivation of their students. Similarly, many college access organizations intentionally match counselors to students based on similarity of backgrounds or interests, hoping that shared experiences will result in a better match and a higher likelihood of helping the student.

BL staff follow a different approach, essentially assigning students to counselors at random. BL staff describe the Access counselor assignment process as a "pretty blind assignment to fill each counselor's caseload (when they come in and who is available to meet with them)." While no formal randomization procedure is followed, this discussion suggests that student assignment to counselor may be as good as random.

We explore this notion more formally in Appendix B, providing a variety of evidence of the quasi-random assignment of students to counselors. Having established quasi-random assignment, we proceed with an investigation of the effects of counselor characteristics and behaviors on student success (details in Appendix B). We find no observable relationship between counselor gender or race and student success (Table 8).[9] While interesting in its own right, the lack of heterogeneity across different types of counselors further suggests the scalability of the program. The BL model appears to work for nearly all counselors, and there is little relationship between counselor characteristics and counselor effectiveness.

5.3 Explaining Growing Effects

While the survey and interaction data provide some indication of why BL Access counselors are effective, they provide little insight into why the effects of BL on enrollment grow over time when nearly every other programs' effects fade. Given BL's emphasis on advising students to make good college choices, one possibility is that treated students are simply more likely to attend colleges where they are likely to succeed. While we already know that treated students are more likely to attend four-year colleges, Table 9 illustrates how other characteristics of the colleges enrolled in by treatment and control students differ. Treated students are 10 percentage points more likely to attend a BL target college. In line with BL's goals, treated students are more likely to attend colleges with higher graduation rates, lower default rates, and higher aptitude students (as measured by SAT and/or ACT scores). [10] Given recent evidence on the role of college choice in influencing graduation rates, the shift to higher graduation rate colleges may account for some part of the growing treatment effects.

Of course, BL's effects on enrollment may also grow over time because many students receive continued on-site counseling through BL's success program. Indeed, in Table 10 we see that conditional on enrollment in the first year after high school, treated students are

[9] There is some suggestive evidence that assigning a student to a counselor who tends to have more application meetings with their assignees may increase the likelihood that that student goes to college, suggesting that BL's increased focus on this aspect of counseling may be important. While it is clear that counselors that have more application meetings are more effective, the results merely suggest that the extent of interaction is causing the higher enrollment rates. It may be that counselors who have more application meetings have some other characteristics that makes them a better counselor.

[10] While they are also more likely to attend more expensive colleges, the very low family income of sample students suggests that sticker (and even net price) are unlikely to be accurate indicators of the true prices faced by students.

4.3 percentage points more likely to remain in college the following year. This is despite the fact that BL likely drew more marginal students into college. When we control for baseline student characteristics, the point estimate grows to 4.7 percentage points. In columns (3) and (4), we compare the persistence of students in the treatment and control group, conditional on enrollment at a non-target college. Here we see small and insignificant differences in persistence that are attenuated upon the inclusion of baseline covariates. In columns (5) and (6) we present analogous estimates for individuals enrolled at BL target college. Here, we see a 6.3 pp difference in persistence when comparing students initially assigned to treatment and control. It is worth stating explicitly that these are no longer experimental estimates as we are conditioning on endogenous variables (selection into different types of colleges). That said, the difference in persistence rates grows (to 6.7 pp) when we condition on baseline covariates (column (6)), suggesting that the BL model induced students who would otherwise have been less likely to persist to attend BL target colleges. Despite this negative selection, treatment group students are more likely to persist.

In columns (7) and (8) we attempt to disentangle the contributions of college quality and ongoing access to counselors to the differential persistence of treatment group students at BL target colleges. Column (7) presents estimates that condition on our measures of college quality and net price. These controls have essentially no effect on the differential persistence of treatment group students, suggesting that differences in college quality are not driving differential persistence. Column (8) conditions on college fixed effects, illustrating that treatment group students are 6.8 pp more likely to persist than control group students *at the same college*. Given the negative selection of treated students (relative to control students) into BL target colleges, we interpret this as a likely lower bound for the effectiveness of the continued counseling presence at BL target colleges.

6 Discussion

Through a multi-cohort, multi-site RCT, we find that the BL college counseling model leads to large positive increases in overall college enrollment and in the quality of institution where students matriculate. In contrast to many other college access and success interventions, BL impacts appear to persist and grow over time, which appears to be driven by the ongoing college counseling BL provides to students who attend one of their target institutions. Our results build on prior experimental studies of college advising programs in several important ways. Ours is the first evaluation of which we are aware that investigates an advising program that provides intensive advising during both high school and throughout college (for most BL students), and ours is the first paper of which we are aware the finds substantial increases in continuous enrollment for the overall sample, effects that appear to grow over time. Second, our paper focuses exclusively on the impact of intensive college advising programs, whereas other studies (e.g. Carrell and Sacerdote, 2017) investigate a combination of advising and financial supports for students such as application fee waivers. Given evidence that even very small differences in costs can affect students' engagement in college planning (Pallais, 2015), it is important to separate the impact of advising from the impact of relaxing financial constraints. Third, our survey results, detailed counselor-student interaction data, and quasi-random counselor assignment indicate that the program has little effect on FAFSA filing, but instead works by altering application behavior, helping students balance cost and quality considerations in choosing where to enroll, and providing ongoing support while students are in college.

Finally, the consistency of our results across space, time, counselors, and students indicate that the BL model provides a scalable solution to closing the income gap in college enrollment and success. We find that BL generates similarly sized impacts across multiple program sites operating in different states under local program leadership. The New York site had been in operation for only a few years prior to the RCT. Large positive effects of the

BL model there provide direct evidence of scalability and suggest that the program reaches maturity and efficacy more rapidly than many other programs. We also find that BL impacts are quite consistent across student sub-groups. This suggests that the BL model has the potential to maintain its positive impact with diverse populations in numerous settings.

We believe it is particularly noteworthy how consistent BL counselors are at improving student outcomes. As we demonstrate above, over 90 percent of BL counselors generated positive postsecondary impacts for the students they served. From a scalability perspective this is highly important, since it suggests that a combination of coherent organizational leadership, successful staff recruitment and training, and effective curriculum are driving the results we observe, rather than a handful of particularly strong counselors who may be hard to identify and recruit in other contexts.

It is also impressive that BL has generated large and growing impacts on students' postsecondary outcomes given that (1) two of the markets in which it operates (New York and Boston) are fairly saturated with other college advising organizations and (2) that BL's impacts are still positive for students who were already engaged with another college access organization at the time they started working with BL. Many of these organizations assist with FAFSA completion and provide application fee waivers, indicating that the BL model adds value above and beyond such low-touch strategies. BL's impacts could be even larger if applied in communities where students have little/no existing access to college advising supports. Even assuming similar effects in other communities, back of the envelope calculations indicate that if the BL model were adopted broadly it would cut the income gap in four-year college enrollment in half.

While the BL model is effective at improving college access and early persistence, lingering questions remain as to the overall cost-effectiveness of the program as well as the cost-effectiveness of the BL model relative to other strategies to increase college access and success. While it is too early to conduct a careful cost-benefit analysis, the BL model passes a cost-benefit test under very conservative assumptions on the eventual effects on degree completion.[11] Given estimated costs per offered student throughout college of approximately $4,000, the BL model is substantially more cost-effective than financial aid. While a number of other counseling programs are cheaper, the heterogeneity and fadeout of enrollment effects makes it difficult to estimate cost-effectiveness. Finally, it is worthwhile to contrast the magnitude of BL's impacts with nudge strategies to improve college access and success. Most of the existing nudge work finds substantially more modest impacts on college enrollment, and it is not yet clear whether these results persist over any length of time. While nudges are a valuable option for educators and policy makers given their low cost and scalability, it's not entirely clear that these strategies are effective at meaningfully improving college completion and in turn economic opportunity for low-income populations. While programs like BL are more resource intensive, our results indicate that successful high-impact advising strategies could play an important role in reducing inequality in American higher education.

[11]BL costs approximately $4,000 per offered student (including both the initial high school counseling and the continued college counseling). If we assume that the 10 percentage point increase in continuous enrollment translates into only a 5 percentage point impact on degree receipt, this suggests that the cost per additional degree completed would be $80,000 ($4,000/.05). Given that the annual earnings premia for a bachelor's degree versus some college is $14,000 (College Board), BL's benefits should exceed costs within several years. Of course, if BL's impact on degree completion is larger than 5 percentage points its benefits should exceed costs more rapidly.

References

Avery, C. (2010): "The effects of college counseling on high-achieving, low-income students," Discussion paper, National Bureau of Economic Research.

——— (2013): "Evaluation of the College Possible program: Results from a randomized controlled trial," Discussion paper, National Bureau of Economic Research.

——— (2014): "The Amherst Telementoring Program for High-Achieving, Low-Income Students: Results of a Pilot Study with a Randomized Controlled Trial," *Havard Kennedy School Faculty Research Working Paper Series.*

Bailey, M. J., and S. M. Dynarski (2011): "Gains and gaps: Changing inequality in US college entry and completion," Discussion paper, National Bureau of Economic Research.

Belley, P., and L. Lochner (2007): "The changing role of family income and ability in determining educational achievement," *Journal of Human capital*, 1(1), 37–89.

Bos, J. M., J. Berman, T. J. Kane, and F. M. Tseng (2012): "The Impacts of SOURCE: A Program to Support College Enrollment through Near-Peer, Low-Cost Student Advising," in *Association of Public Policy Analysis and Management Annual Conference.*

Carrell, S. E., and B. Sacerdote (2017): "Why Do College-Going Interventions Work?," *American Economic Journal: Applied Economics*, 9(3), 124–51.

Castleman, B., and J. Goodman (2016): "Intensive College Counseling and the Enrollment and Persistence of Low Income Students," *Education Finance and Policy.*

Chetty, R., J. N. Friedman, E. Saez, N. Turner, and D. Yagan (2017): "Mobility report cards: The role of colleges in intergenerational mobility," Discussion paper, National Bureau of Economic Research.

Constantine, J., N. Seftor, E. S. Martin, T. Silva, D. Myers, et al. (2006): "A study of the effect of Talent Search on secondary and postsecondary outcomes in Florida, Indiana, and Texas," Discussion paper, Mathematica Policy Research.

Dynarski, S. M., S. W. Hemelt, and J. M. Hyman (2015): "The missing manual: Using National Student Clearinghouse data to track postsecondary outcomes," *Educational Evaluation and Policy Analysis*, 37(1_suppl), 53S–79S.

Goodman, J., M. Hurwitz, and J. Smith (2017): "Access to 4-Year Public Colleges and Degree Completion," *Journal of Labor Economics*, 35(3), 000–000.

Hoekstra, M. (2009): "The effect of attending the flagship state university on earnings: A discontinuity-based approach," *The Review of Economics and Statistics*, 91(4), 717–724.

Hoxby, C., S. Turner, et al. (2013): "Expanding college opportunities for high-achieving, low income students," *Stanford Institute for Economic Policy Research Discussion Paper*, (12-014).

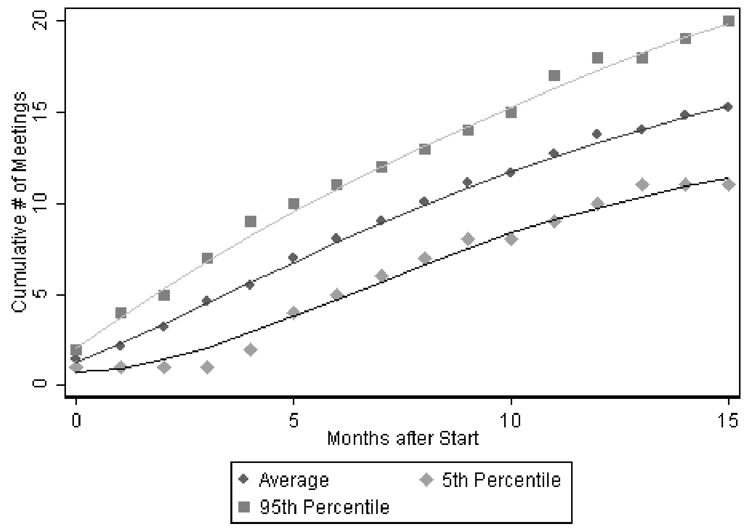
Pallais, A. (2015): "Small differences that matter: Mistakes in applying to college," *Journal of Labor Economics*, 33(2), 493–520.

Seftor, N. S., A. Mamun, A. Schirm, et al. (2009): "The impacts of regular Upward Bound on postsecondary outcomes 7-9 years after scheduled high school graduation," *Washington, DC: US Department of Education, Policy and Program Studies Service.*

Stephan, J. L., and J. E. Rosenbaum (2013): "Can high schools reduce college enrollment gaps with a new counseling model?," *Educational Evaluation and Policy Analysis*, 35(2), 200–219.

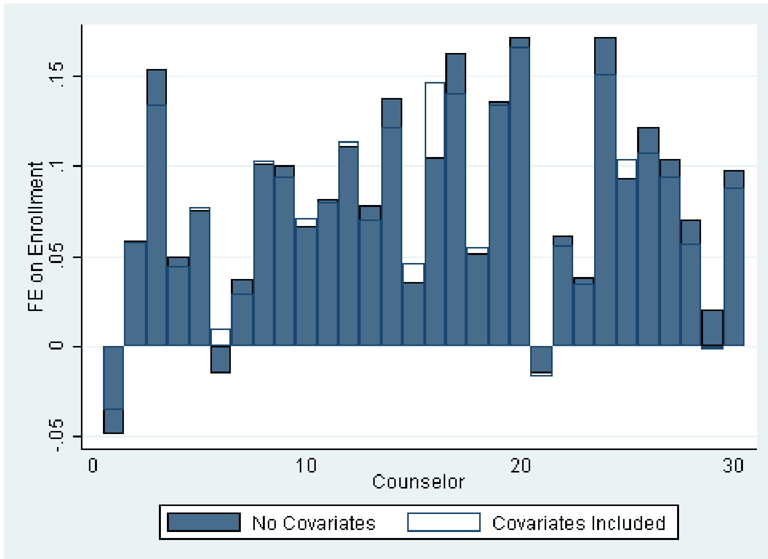
Zimmerman, S. D. (2014): "The returns to college admission for academically marginal students," *Journal of Labor Economics*, 32(4), 711–754.

Figure 1: Counselor Interaction Patterns over Time

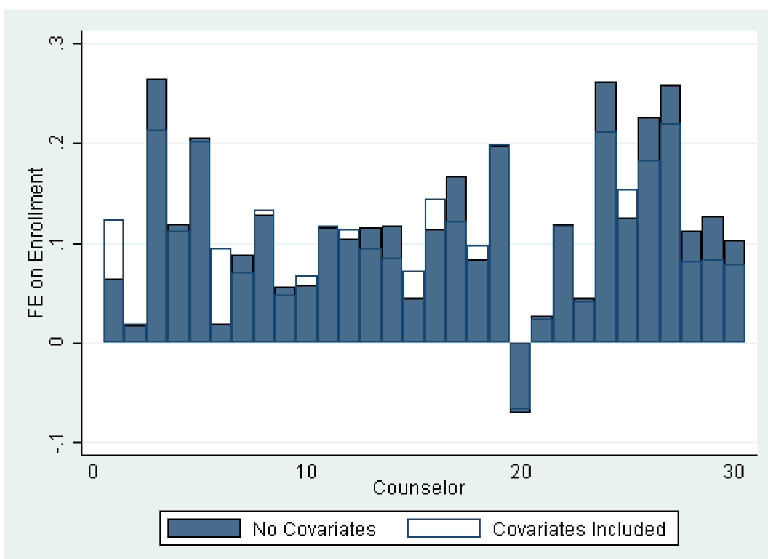


Note: Statistics derived from BL data. Month 0 is May of each high school class' junior year.

Figure 2: Counselor Fixed Effect Estimates



(A) College Enrollment



(B) Four-Year College Enrollment

*Note:*Estimates derived from basic specification but replacing treatment indicator with counselor fixed effects.

Table 1: Descriptive Statistics and Randomization Tests

	Full Sample		Cohort 1		Cohort 2	
	Control Mean (1)	Treatment (2)	Control Mean (3)	Treatment (4)	Control Mean (5)	Treatment (6)
Female	0.697	0.004	0.703	-0.008	0.688	0.001
		(0.021)		(0.027)		(0.033)
Black	0.302	0.022	0.295	0.027	0.312	0.015
		(0.021)		(0.027)		(0.034)
Hispanic	0.325	-0.008	0.334	.03	0.312	.027
		(0.021)		(0.028)		(0.033)
Asian	0.246	-0.009	0.251	.008	0.239	-0.035
		(0.020)		(0.026)		(0.030)
Other Race	0.094	0.001	0.092	.004	0.096	-0.000
		(0.014		(0.017)		(0.022)
Citizen	0.787	-0.039**	0.788	-0.065***	0.785	0.001
		(0.019)		(0.025)		(0.030)
Verified GPA	3.264	-0.004	3.266	-0.008	3.260	0.001
		(0.027)		(0.032)		(0.046)
Parent AGI	22520	393	21424	970	24112	-455
		(840)		(1054)		(1380)
Household Size	4.26	-0.003	4.27	-0.034	4.25	.042
		(0.074)		(0.095)		(0.119)
Mom Employed	0.641	.005	0.640	0.013	0.642	-0.008
		(0.023)		(0.030		(-.037)
Mom Employed (missing)	0.144	-0.007	0.143	-0.003	0.146	-0.012
		(0.016)		(0.020)		(-.025)
Dad Employed	0.693	0.063**	0.683	0.080**	0.705	0.040
		(.028)		(.037)		(.042)
Dad Employed (missing)	0.446	-0.004	0.484	-0.021	0.392	0.020
		(.023)		(-0.021)		(0.035)
First Generation	0.811	.000	0.820	-0.007	0.797	0.011
		(.019)		(0.024)		(.0302)
Sibling College	0.389	-0.004	0.390	-0.003	0.387	-0.004
		(.023)		(0.030)		(0.036)
Sibling College (missing)	0.059	-0.011	0.055	-0.008	0.063	-0.015
		(.010)		(.013)		(0.017)
Sibling Bottom Line	0.075	.001	0.067	-0.002	0.086	-0.009
		(.013)		(0.016)		(0.021)
Sibling Bottom Line (missing)	0.074	-0.001	0.071	-0.002	0.076	-0.000
		(0.012)		(0.015)		(0.019)
Other Program	0.444	-0.009	0.189	-0.017	0.415	0.002
		(.022)		(.029)		(0.035)
Observations		2422		1429		993

Note: Odd columns contain control group means. Each cell in even columns contains a coefficient from a separate regression of the observed characteristics on a treatment indicator variable, controlling for site by cohort (i.e., risk set) indicators. Robust standard errors in parentheses. * (p<0.10) **(p<0.05), ***(p<0.01).

Table 2: Counselor Interaction Patterns

	Mean
Ever Interact with Student (proportion):	0.97
Office Meeting	0.95
Phone Meeting	0.32
Interactions per Student (number):	13.06
By Medium:	
Office Meeting	8.81
Phone Meeting	0.42
Text or Email	0.28
By Subject:	
First Meeting	2.13
Second Meeting	1.37
Application Meeting	3.47
Financial Aid Meeting	2.03
Missed Meetings	0.59
Estimated Contact Time per Student (hours):	10-15

Note: Statistics calculated from BL data. Sample for rows (1)-(3) includes all students assigned to treatment and has a sample size of 1687. Remaining rows are restricted to the 97.2 percent of students assigned to treatment who had any post-assigment interaction with BL. Sample size for these rows is 1639.

Table 3: Effects on Enrollment in College

	Full Sample		Cohort 1		Cohort 2	
	Control Mean (1)	Treatment (2)	Control Mean (3)	Treatment (4)	Control Mean (5)	Treatment (6)
Enrolled Any College	0.827	0.070***	0.841	0.055***	0.807	0.091***
		(0.016)		(0.020)		(0.026)
Enrolled 4-Year College	0.703	0.103***	0.712	0.104***	0.691	0.104***
		(0.019)		(0.024)		(0.030)
Enrolled 2-Year College	0.127	-0.034**	0.129	-0.049***	0.123	-0.016
		(0.014)		(0.019)		(0.022)
Observations		2422		1429		993

Note: Odd coluns contain control group means. Each cell in even columns contains a coefficient from a separate regression of each outcome variable (indicated by the row title) on a treatment indicator variable, controlling for site by cohort (i.e., risk set) indicators as well as the covariates indicated in Table 1. Robust standard errors in parentheses. * (p<0.10) **(p<0.05), ***(p<0.01).

Table 4: Effects on Enrollment in College: Heterogeneity

	Female		Black		Hispanic		No Other Program		Low GPA		Low AGI	
	Mean	Treatment	Mean	Treatment	Mean	Treatment	Mean	Treatment	Mean	Treatment	Mean	Treatment
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Enrolled Any College	0.834	0.072***	0.820	0.075**	0.816	0.082***	0.848	0.056***	0.758	0.097***	0.809	0.078***
		(0.018)		(0.030)		(0.029)		(0.020)		(0.026)		(0.023)
Enrolled 4-Year College	0.701	0.117***	0.703	0.100***	0.649	0.128***	0.716	0.101***	0.579	0.122***	0.682	0.113***
		(0.023)		(0.035)		(0.035)		(0.025)		(0.030)		(0.027)
Enrolled 2-Year College	0.135	-0.046**	0.117	-0.023	0.172	-0.049*	0.134	-0.047**	0.184	-0.027	0.130	-0.037*
		(0.018)		(0.025)		(0.028)		(0.019)		(0.024)		(0.020)
Observations		1639		784		736		1359		1179		1205

Note: Odd columns contain control group means for each subsample. Each cell in even columns contains a coefficient from a separate regression of each outcome variable (indicated by the row title) on a treatment indicator variable, controlling for site by cohort (i.e., risk set) indicators as well as the covariates indicated in Table 1. Robust standard errors in parentheses. * (p<0.10) **(p<0.05), ***(p<0.01).

Table 5: Effects on Persistence in College

	Cohort 1	
	Control Mean (1)	Treatment (2)
Enrolled Any College (2nd Year)	0.790	0.080***
		(0.023)
Enrolled 4-Year College (2nd Year)	0.634	0.143***
		(0.026)
Enrolled 2-Year College (2nd Year)	0.159	-0.062***
		(0.020)
Total Enrolled Semesters	2.45	0.199***
		(0.054)
Continuously Enrolled	0.705	0.099***
		(0.025)
Observations		1429

Note: Odd columns contain control group means. Each cell in even columns contains a coefficient from a separate regression of each outcome variable (indicated by the row title) on a treatment indicator variable, controlling for site by cohort (i.e., risk set) indicators as well as the covariates indicated in Table 1. Robust standard errors in parentheses. * ($p<0.10$) **($p<0.05$), ***($p<0.01$).

Table 6: Effects on Persistence in College: Heterogeneity

	Female		Black		Hispanic		No Other Program		Low GPA		Low AGI	
	Mean	Treatment	Mean	Treatment	Mean	Treatment	Mean	Treatment	Mean	Treatment	Mean	Treatment
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Enrolled	0.800	0.077***	0.766	0.102**	0.793	0.069*	0.800	0.078***	0.702	0.112***	0.796	0.051
		(0.026)		(0.044)		(0.040)		(0.029)		(0.038)		(0.033)
Enrolled 4-Year	0.633	0.145***	0.648	0.104***	0.586	0.158***	0.650	0.126***	0.488	0.173***	0.620	0.129***
		(0.031)		(0.049)		(0.046)		(0.033)		(0.040)		(0.037)
Enrolled 2-Year	0.170	-0.070***	0.117	0.001	0.207	-0.087**	0.150	-0.044*	0.215	-0.057*	0.181	-0.081***
		(0.026)		(0.035)		(0.037)		(0.025)		(0.032)		(0.029)
Total Enrolled Semesters	2.436	0.220***	2.438	0.193*	2.428	0.176*	2.450	0.211***	2.234	0.249***	2.385	0.211****
		(0.063)		(0.106)		(0.096)		(0.069)		(0.091)		(0.082)
Continuously Enrolled	0.702	0.102***	0.688	0.121**	0.690	0.083*	0.700	0.112***	0.600	0.128***	0.692	0.083**
		(0.030)		(0.048)		(0.045)		(0.032)		(0.041)		(0.037)
Observations		985		448		425		815		704		714

Note: Odd columns contain control group means for each subsample. Each cell in even columns contains a coefficient from a separate regression of each outcome variable (indicated by the row title) on a treatment indicator variable, controlling for site by cohort (i.e., risk set) indicators as well as the covariates indicated in Table 1. Robust standard errors in parentheses. * (p<0.10) **(p<0.05), ***(p<0.01).

Table 7: Spring of Senior Year Survey (first cohort)

	Control Mean (1)	Treatment (2)
Proportion Applying	0.988	0.009
		(0.007)
Number of Applications	9.75	2.91***
		(0.336)
Costs Important	0.50	0.09*
		(0.05)
Filled Out FAFSA	0.97	0.017
		(0.05)
Met to Review Award Letter	0.66	0.18*
		(0.09)
College Access Advisor Important	0.21	0.37*
		(0.22)
Observations		814

Note: Odd columns contain control group means for each subsample. Each cell in even columns contains a coefficient from a separate regression of each variable (indicated by the row title) on a treatment indicator variable, controlling for site by cohort (i.e., risk set) indicators as well as the covariates indicated in Table 1. Robust standard errors in parentheses. * (p<0.10) **(p<0.05), ***(p<0.01).

Table 8: Relationship Between Counselor Characteristics and Enrollment Outcomes

	Enrolled		Enrolled 4-Year		Semesters		Cont. Enrolled	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Counselor Characteristics								
Female	0.003	0.004	-0.041	-0.045	-0.028	-0.028	0.004	0.003
	(0.037)	(0.036)	(0.048)	(0.046)	(0.076)	(0.075)	(0.036)	(0.036)
Black	-0.014	-0.015	-0.037	-0.035	-0.074	-0.073	-0.024	-0.022
	(0.029)	(0.029)	(0.039)	(0.037)	(0.061)	(0.060)	(0.029)	(0.029)
White	0.014	0.02	0.023	0.037	0.04	0.052	0.013	0.017
	(0.030)	(0.030)	(0.040)	(0.038)	(0.063)	(0.062)	(0.030)	(0.030)
Hispanic	0.02	0.022	0.03	0.036	0.054	0.059	0.015	0.017
	(0.032)	(0.032)	(0.042)	(0.040)	(0.066)	(0.065)	(0.032)	(0.032)
Application Meetings	0.062*	0.063*	0.066	0.073	0.123	0.123	0.047	0.049
	(0.037)	(0.037)	(0.048)	(0.047)	(0.076)	(0.075)	(0.037)	(0.036)
Financial Aid Meetings	-0.028	-0.026	-0.096	-0.092	-0.183	-0.18	-0.05	-0.049
	(0.059)	(0.058)	(0.077)	(0.074)	(0.122)	(0.120)	(0.058)	(0.058)
Covariates		X		X		X		X

Note: Each column contains estimates from a separate regression of a dependent variable (in columns) on a set of counselor characteristics. Application meetings and financial aid meetings variables provide a measure of the average number of meetings of each type per student for each counselor. The variable is constructed using a leave one out procedure, so that each individual is assigned the average number of meetings occurring between every other student with the same counselor. Robust standard errors in parentheses. * ($p<0.10$) **($p<0.05$), ***($p<0.01$).

Table 9: Effect of BL on College Choice

VARIABLES	(1) Target	(2) Tuition and Fees	(3) Net Price	(4) Net Price (0-48K)	(5) Grad. Rate	(6) Default Rate	(7) SAT 25	(8) SAT 75	(9) ACT 25	(10) ACT 75
Treatment	0.10***	1,764***	1,023**	369	5.37***	-1.15***	21.69***	21.27***	0.688***	0.591***
	(0.022)	(644)	(401)	(323)	(0.997)	(0.207)	(6.80)	(6.91)	(0.230)	(0.215)
Observations	2,422	2,089	2,074	2,079	2,074	2,074	1,662	1,662	1,084	1,084
Control Mean	0.44	14886	13981	10868	47.70	9.157	983.2	1180	22.26	26.78

Note: Each column contains a regression of a different dependent variable on the full set of covariates, controlling for site by cohort indicators. Robust standard errors in parentheses. * (p<0.10) **(p<0.05), ***(p<0.01).

Table 10: Effects on Persistence in College (conditional on first-year enrollment)

	All Schools		Not Target		BL Target			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	0.043**	0.047**	0.022	0.015	0.063**	0.067**	0.070**	0.068**
	(0.020)	(0.020)	(0.026)	(0.026)	(0.031)	(0.031)	(0.031)	(0.031)
Covariates		X		X		X	X	X
College Covariates							X	
College FEs								X
Observations	1,261	1,261	595	595	666	666	666	666
Control Mean	0.88	0.88	0.89	0.89	0.86	0.86	0.86	0.86

Note: Each column contains estimates from a separate regression of enrollment in the second year, controlling for site by cohort (i.e., risk set) indicators. Individual covariates are as in Table 1. College covariates (net price for students with income between 0 and $48,000, graduation rate, default rate, SAT and ACT measures, and the associated missing variable indicators). To support estimation, specifications with college fixed effects (columns (11) and (12)) are restricted to colleges with first-year fall enrollment of at least four control group students. Robust standard errors in parentheses. (p<0.10) **(p<0.05), ***(p<0.01).

Appendix A: Supplemental Tables

Table A1: Encouraged Colleges

College Names	Graduation Rate	Tuition and Fees	Net Price (0-48K)
Bentley University	84.1	41110	20544
Boston College	92.2	45622	16196
Boston University	83.9	44910	23573
Bridgewater State University	54.4	8053	14680
Buffalo State SUNY	48.1	7022	8021
CUNY Hunter College	45.7	6129	5258
CUNY John Jay College of Criminal Justice	43.1	6059	3993
CUNY Lehman College	34.9	6108	3297
CUNY New York City College of Technology	13.6	6069	5220
CUNY York College	25.6	6096	4590
Clark University	79.8	39550	18293
College of the Holy Cross	92.9	44272	15607
Fitchburg State University	50.8	8985	9013
Fordham University	81	43577	23352
Framingham State University	51.5	8080	12515
MCPHS University	66.4	28470	29807
Northeastern University	78.5	41686	20140
SUNY at Albany	64.4	8040	11019
Saint Joseph's College-New York	67.5	21878	10292
Salem State University	45.4	8130	11800
St Francis College	51.9	20700	9448
State University of New York at New Paltz	72.7	7083	9844
Suffolk University	55.9	31716	22900
The Sage Colleges	51.8	28000	14834
University of Massachusetts-Amherst	70.4	13258	12437
University of Massachusetts-Boston	37.9	11966	8084
University of Massachusetts-Dartmouth	49.9	11681	12581
University of Massachusetts-Lowell	53.8	12097	10258
Wentworth Institute of Technology	64	29200	25754
Worcester Polytechnic Institute	83.5	42778	27224
Worcester State University	51	8157	10907
Mean	59.6	20854	13919

Table A2: Experimental Design

	Boston	New York	Worcester	Total
Control	193	450	92	735
Treatment	860	582	245	1,687

Appendix B: Quasi-random Counselor Assignment

We explore the notion of random assignment of students to counselors more formally by conducting a set of randomization tests. In Table B1, we explore the relationship between a number of counselor characteristics and baseline student characteristics. Formally, we estimate the following specification:

$$C_i = \alpha + \beta X_i + \sum_j \gamma_j l_{ij} + \varepsilon_i \tag{2}$$

where C_i are observable demographic characteristics of the counselors and measures of the extent to which a counselor meets with his or her assigned students, and X_i includes baseline demographic student characteristics. The l_{ij} are site by cohort fixed effects which control for site by cohort variation in the pool of students randomized across counselors.

The counselor interaction measures (in columns(6) through (9), indicate the average number of meetings of each type that a counselor holds over the course of the program. For example, the dependent variable in column (6) is the average number of meetings about applications that a counselor has had with each of his or her students. We follow a leave-one-out procedure to eliminate the possibility that a particular student could influence his or her counselor's score via their own behavior; thus, our variable of interest takes the form $X_{-i,s}$. The estimates in Table B1 suggest little relationship between counselor observables characteristics (or behavior) and baseline individual student characteristics, supporting the argument that counselors are as good as randomly assigned. F tests for the joint significant of all the pre-determined variables are generally insignificant, illustrating that particular types of students do not appear to be assigned to particular types of counselors.[12] Similarly, columns (6)-(9) indicate that particular types of students do not appear to be assigned to counselors who exhibit different counseling tendencies. This suggests that students are as

[12]The lone exception is for white counselors, a result that appears to be driven by white counselors adjusting verified GPAs rather than non-random assignment. If we exclude verified GPA from the regression, the remaining variables are not predictive of having a white counselor.

good as randomly assigned to counselors.

In Table 8, we explore whether our measures of counselor characteristics and behavior are predictive of college enrollment and success. There are no statistically significant relationships between counselor observables or behavior and student access, with the point estimates on application meetings suggesting that counselors that hold more application meetings may be more effective.[13]

[13] As further evidence of random assignment to counselors, we present estimates of the relationship between counselor characteristics and a predicted index in Table B2. The predicted indexes are constructed by regressing the outcome measure indicated on the full set of baseline student characteristics as well as site by cohort indicators. In contrast to the effect on actual outcomes, there is no effect of application meeting behavior on any our predicted indexes.

Table B1: Tests of Random Counselor Assignment

Couns. Chars.	(1) Female	(2) Black	(3) White	(4) Hispanic	(5) # of App.	(6) # of Fin. Aid	(7) # of Office	(8) # of Contacts
Baseline Covariates:								
Parent AGI	-0.000	0.000	-0.000	-0.000	-0.000	-0.000	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
Household Size	0.006	-0.002	0.012**	0.001	0.005	-0.001	0.006	-0.002
	(0.007)	(0.006)	(0.006)	(0.007)	(0.005)	(0.005)	(0.010)	(0.015)
Verified GPA	-0.008	0.014	-0.022	-0.014	-0.021	-0.002	-0.057*	-0.120***
	(0.020)	(0.018)	(0.018)	(0.020)	(0.014)	(0.013)	(0.030)	(0.045)
Female	0.013	-0.006	0.032	-0.030	0.030*	0.018	0.072**	0.087
	(0.024)	(0.021)	(0.021)	(0.023)	(0.016)	(0.016)	(0.036)	(0.053)
White or Asian	-0.006	-0.037	0.023	0.034	0.030	0.025	0.057	0.108
	(0.042)	(0.038)	(0.038)	(0.042)	(0.029)	(0.028)	(0.063)	(0.094)
Black	-0.062	0.027	0.015	-0.016	-0.038	0.013	-0.021	-0.014
	(0.041)	(0.036)	(0.036)	(0.040)	(0.028)	(0.026)	(0.061)	(0.090)
Hispanic	-0.053	0.002	0.007	-0.008	-0.018	-0.006	-0.051	-0.036
	(0.041)	(0.037)	(0.037)	(0.041)	(0.028)	(0.027)	(0.062)	(0.091)
Observations	1,596	1,596	1,596	1,596	1,596	1,596	1,596	1,596
R-squared	0.007	0.008	0.013	0.005	0.010	0.004	0.010	0.009
Prob>F	0.362	0.262	0.0208	0.702	0.0912	0.728	0.106	0.155
Mean	0.727	0.228	0.281	0.282	3.591	2.121	9.151	13.58

Note: Each column contains a regression of a different counselor characteristic on the full set of covariates, controlling for site by cohort indicators. The average # of meetings variables are constructed using a leave one out procedure, so that each individual is assigned the average number of meetings occurring between every other student with the same counselor. Robust standard errors in parentheses. * (p<0.10) **(p<0.05), ***(p<0.01).

Table B2: Placebo Checks: Relationship Between Counselor Characteristics and *Predicted** Enrollment Outcomes

	Index Enrolled (1)	Index Enrolled 4-Year (2)	Index Semesters (3)	Index Cont. Enrolled (4)
<u>Counselor Characteristics</u>				
Female	-0.001	0.001	-0.001	0.001
	(0.002)	(0.006)	(0.007)	(0.004)
Black	-0.001	-0.003	-0.005	-0.002
	(0.003)	(0.007)	(0.010)	(0.005)
White	-0.004	-0.006	-0.01	-0.003
	(0.003)	(0.007)	(0.009)	(0.004)
Hispanic	-0.002	-0.007	-0.008	-0.004
	(0.003)	(0.007)	(0.010)	(0.005)
$Avg.\ App\ Meetings_{-i}$	0.001	-0.002	0.002	-0.001
	(0.003)	(0.007)	(0.009)	(0.005)
$Avg.\ Fin\ Aid\ Meetings_{-i}$	0.002	0.004	0.008	0.005
	(0.003)	(0.006)	(0.008)	(0.004)

Note: * The predicted indexes are constructed by regressing the outcome measure indicated on the full set of baseline covariates as well site by cohort indicators. Each column contains estimates from a separate regression of a dependent variable (in columns) on a set of counselor characteristics. Application meetings and financial aid meetings variables provide a measure of the average number of meetings of each type per student for each counselor. The variable is constructed using a leave one out procedure, so that each individual is assigned the average number of meetings occurring between every other student with the same counselor. Robust standard errors in parentheses. * (p<0.10) **(p<0.05), ***(p<0.01).