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INCREASING DEGREE ATTAINMENT AMONG LOW-INCOME STUDENTS: THE ROLE OF INTENSIVE ADVISING AND COLLEGE QUALITY

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ABSTRACT

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A data appendix is available at http://www.nber.org/data-appendix/w33921

Increasing Degree Attainment Among Low-Income Students: The Role of Intensive Advising and College Quality*

By Andrew Barr and Benjamin Castleman

Abstract

A college degree offers a pathway to economic mobility for low-income students. Using a multi-site randomized controlled trial combined with administrative and survey data, we demonstrate that intensive advising during high school and college significantly increases bachelor's degree attainment among lower-income students. We leverage unique data on pre-advising college preferences and causal forest methods to show that these gains are primarily driven by improvements in initial enrollment quality. Our results suggest that strategies targeting college choice may be a more effective and efficient means of increasing degree attainment than those focused solely on affordability.

A college education remains an effective channel through which children born into low-income families can achieve greater economic opportunity. At the same time, socioeconomic and racial gaps in college completion are wide; while half of people from high-income families obtain a bachelor's degree by age 25, only one in ten people from low-income families do (Bailey and Dynarski 2011). Large gaps in degree attainment also exist when comparing across racial and ethnic groups. Differences in preparation explain some of the attainment gaps, but disparities in college success by family income persist even upon controlling for academic achievement (Bailey and Dynarski 2011; Belley and Lochner 2007).

A growing body of research suggests that students are more likely to earn a degree and to realize better labor market outcomes when they attend higher-quality colleges and universi-

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ties (Goodman, Hurwitz, and Smith 2020; Hoekstra 2008; Zimmerman 2014).[1] But numerous barriers may prevent students, particularly those from lower-income and less-educated backgrounds, from enrolling in higher-quality colleges and universities. While some students do not meet admissions criteria (as in the aforementioned studies), others may *choose* not to apply or attend due to a lack of information about differences in college quality and the likelihood of acceptance at higher-quality institutions; over-estimation of college costs and a lack of awareness about financial aid eligibility; and/or limited understanding of or confusion about the college and financial aid application process (Avery and Kane 2004; Bettinger et al. 2012; Dynarski and Scott-Clayton 2006; Hoxby and Avery 2013). Indeed, recent work provides compelling evidence that reducing uncertainty about the quality, costs, and likelihood of admission to highly selective institutions (e.g., Harvard, Stanford, or University of Michigan) can be effective in improving enrollment quality among high-achieving, low-income students (Dynarski et al. 2021; Hoxby and Turner 2013). But low-income students with the necessary scores to be considered for admission at these high-quality and low-cost (net of financial aid) institutions account for less than one percent of the U.S. high school population.

The vast majority of low-income students, on the other hand, face choice sets where the optimal combination of quality and affordability is unclear. As illustrated in Appendix Figure A1, there is tremendous variation in the graduation rates and average net prices of colleges attended by low-income students.[2] The challenge low-income students face to optimize quality and affordability in their college search and selection is exacerbated by the limited support they typically receive with the college application process within high school. The average public high school counselor has roughly 300 students on their caseload, and spends less than 19 percent of their time on college counseling (Gagnon and Mattingly 2016;

[1] These studies leverage variation in whether students are just above score-based admissions criteria to attend four-year institutions. In line with these findings, recent work indicates that students diverted from 4-year to 2-year institutions are less likely to earn degrees and have lower earnings (Mountjoy 2022).

[2] For example, among students attending colleges or universities with a graduation rate of 60 percent, average net prices for low-income students range from roughly \$7,000 to \$24,000.

Clinedinst 2019).[3] Caseloads are higher (and time spent on college counseling is lower) in districts serving higher shares of low-income or non-white students.

College advising programs are an important supplement to help students navigate the college choice process, especially in the absence of more robust college counseling within high schools. These initiatives are widespread – college advising organizations serve two million students each year (more than half the number of high-school graduates).[4] Yet despite the volume of programs and the magnitude of financial investment in these organizations, rigorous evidence of the impact of advising on students' college success and degree attainment is fairly limited. A few studies demonstrate advising leads to increased enrollment in college, but those that track students beyond initial enrollment suggest that these effects may fade (Avery 2013; Bettinger and Evans 2019; Carrell and Sacerdote 2017).[5,6] Our study provides new evidence on the extent to which more intensive college advising *with significant emphasis on college choice* generates increases in bachelor's degree receipt.

We conducted a multi-cohort and multi-site randomized controlled trial of the Bottom Line (BL) college advising program, which operates in several cities in Massachusetts, New York, and Illinois, drawing low-income students from several hundred high schools.[7] The advising model is divided into two distinct stages: Access advising and Success advising. Access advising begins the summer before a student's senior year of high school and contin-

[3] Mulhern (2023) moreover demonstrates that counselors vary in their effectiveness at improving students' behavioral and academic outcomes during and just after high school, with students assigned one of the very best counselors instead of one of the very worst being approximately two percentage points more likely to go to college.

[4] Estimates from the National College Attainment Network (NCAN).

[5] In Avery (2013), the estimated "intent to treat" effect for any enrollment became negative from the fall to spring semester and the estimated effect on four-year enrollment fell roughly a third, from 15.1 to 9.7 percentage points. In Bettinger and Evans (2019), modest initial impacts of 1-2 percentage points (which were primarily on two-year enrollment) dissipated over time with a non-significant 0.6 percentage point increase in the likelihood of enrollment in the second year. In Carrell and Sacerdote (2017), those assigned to treatment were roughly 4 percentage points less likely to be enrolled in the second year, conditional on enrollment in the first year. While the fade out in estimated enrollment effects in these three studies is not precise enough to draw strong conclusions, one potential explanation is that these programs did not focus sufficiently on where students chose to enroll.

[6] Other studies either do not find initial effects of advising or do not track students beyond initial enrollment (Bos et al. 2012; Seftor, Mamun, and Shirn 2009).

[7] BL's site in Chicago opened in 2014 and is not included in our analysis. The organization recently received a $15 million grant to further expand into several cities in Ohio.

ues through the summer after graduation. Advisors provide individualized support, helping students identify well-matched colleges and complete applications. They particularly encourage students to consider four-year institutions that offer an optimal combination of quality and affordability, with a focus on increasing bachelor's degree attainment. A key feature of the BL model is its professionalism, intensity, and duration. Unlike programs relying on part-time staff or volunteers, BL employs salaried advisors, with students spending an average of 10-15 hours working with their advisor before transitioning to college. Success advising is another unique component of the BL model. For students who enroll at a target institution (roughly half of advisees choose to do so), BL continues to provide individualized, campus-based support to students for up to six years following high school.

We find that students randomly offered intensive college advising are substantially more likely to earn a bachelor's degree within 5-6 years of high school. Pooling across experimental cohorts (high school graduating classes of 2015 and 2016), students offered advising were 7.6 percentage points more likely to earn a bachelor's degree within five years of high school; this represents a 16 percent increase relative to the control group. Students in the first experimental cohort were 9.6 percentage points more likely to earn a bachelor's degree within six years of high school, an 18 percent increase relative to the control group. These effects on bachelor's attainment are as large as any rigorous estimates we have come across in the economics literature. In the face of declining social mobility, intensive advising may be an effective policy strategy to promote greater economic opportunity for economically-disadvantaged, academically college-ready students. Indeed, the estimated impact of advising on bachelor's degree attainment is roughly as large as the (conditional on aptitude) gap in degree attainment between children from families in the first and fourth quartile of the income distribution (Belley and Lochner 2007).

What explains the large impact of this advising model on degree attainment? Prior rigorous evaluations of college advising models have been limited in investigating this question empirically. We capitalize on unique access to data on baseline college preferences for the entire experimental sample at the end of the junior year of high school, prior to assignment to treatment, to argue that effective college advising shifts students' choices about where to apply and enroll. First, we use these data to document that many low-income students (between a third and two-thirds) are interested in colleges that appear to be objectively suboptimal.[8] Next, we demonstrate that intensive advising results in large improvements in enrollment quality: pooling across cohorts, students offered intensive advising were 9.1 percentage points (13 percent) more likely to attend four-year institutions, with almost all of this marginal enrollment occurring at institutions with high graduation rates. We moreover present evidence that the effects of advising on measures of initial college quality *and* eventual degree receipt are significantly larger among students with suboptimal baseline interests.

Reinforcing the important role of college quality in promoting bachelor's degree attainment, we apply causal forest methods to demonstrate the strong relationship between the likelihood that intensive advising shifts an individual into a higher quality institution and the likelihood that advising increases that individual's BA attainment (Athey and Imbens 2016; Athey and Wager 2019).[9] Our results suggest that shifts in college quality account for most (roughly 70 percent) of the estimated effect of advising on bachelor's degree attainment, and that access to ongoing advising during college has at most a modest effect on degree attainment. This application of causal forest methods for mediation could be used in numerous other settings where researchers are interested in better understanding the role of mediating factors in driving longer-term impacts, such as disentangling the role of cognitive versus non-cognitive skill improvements in influencing high-school graduation or the commission of crime; the role of different healthcare interventions in subsequent morbidity or mortality; or

[8]For example, many low-income students indicate interest in colleges with high net prices and low measures of quality, or very low graduation rates given students' aptitude and high-school performance.

[9]We provide further explanation of causal forest methods in the Mechanisms section and Appendix B below. One main advantage of our approach is that causal forest methods have greater explanatory power than more common methods to explain treatment effect heterogeneity, allowing for a more informative exploration of the relationships between treatment effects on mediators (e.g., enrollment quality) and treatment effects on ultimate outcomes (e.g., degree attainment.).

the role of neighborhood attributes in influencing a child's subsequent outcomes.

Consistent with the estimated impacts on choice and attainment, student survey responses suggest that advisors' influence likely occurred during the college search and college choice phases. For instance, treated students applied to substantially more colleges and universities, expanding their potential choice set. Qualitative analysis of students' open-ended responses reflecting on their experience applying to college suggest advisors reduced the difficulty and stress of the process, helping students navigate complex decisions such as where to apply. We also find suggestive evidence that treated students may have substituted towards professional, trained college advisors to discuss important aspects of the college and financial aid process, and away from potentially less experienced or informed sources.

Our findings reinforce the importance of personalized coaching in the college application and choice process over much lower-cost alternatives, like informational or "nudge" interventions. Whereas we observe large impacts of intensive advising on enrollment quality that continue through to degree attainment, most informational interventions designed to improve postsecondary outcomes (e.g., FAFSA completion, college enrollment, success among current college students) have had very small or no effect, either among traditional or non-traditional student populations (e.g., Avery et al., 2021; Barr et al., 2024; Bergman, Denning, and Manoli, 2021; Bettinger et al., 2022; Bird et al., 2021; Gurantz et al., 2019). This finding aligns with recent evidence from other policy domains, including housing (e.g., Bergman et al., 2024), benefit take up (Notowigdido and Finkelstein, 2019), job search assistance and training (e.g., Dhia et al. 2022; Card, Kluve, and Weber 2017; Barr and Turner 2018), financial decision-making (e.g., Bai and Massa 2021), and health (e.g., Myerson et al. 2022), which similarly suggest that personalized human support outperforms passive, informational strategies especially in the face of complex decisions or processes. The role of a trusted advisor appears critical to generating meaningful change in students' initial enrollment choices and subsequent degree attainment outcomes.

To put the magnitude of these effects into context, we calculate the additional likelihood of bachelor's degree attainment per $1,000 of spending and compare this cost to other programs (primarily financial aid programs) with rigorous evidence of increasing degree attainment. The scaled effect size of intensive advising appears to be substantially higher than that for programs that provide significant financial assistance for college.[10] Indeed, the advising model appears to be as cost-effective at increasing bachelor's degree attainment as any rigorously evaluated policy of which we are aware. While maintaining implementation quality at scale for intensive advising may be more challenging than for aid programs, the consistency of the results across students, advisors, and sites, including direct evidence of effectiveness in a recent expansion site (NYC), point to the potential of the advising model to be replicated and expanded to other contexts. More generally, strategies that improve the quality of the colleges attended by low-income students, such as intensive advising, likely have the most potential to improve degree attainment.

I Background

Bottom Line (BL) began in Boston in 1997 and now operates programs in Boston, Worcester (MA), New York City, and Chicago. We first describe BL's recruitment and application process. We then describe the key programmatic features of the Access program, through which BL provides advising to students while they are still in high school. Finally, we describe the programmatic features of the Success program, which serves students who attend one of BL's target colleges or universities.

[10] Aid programs increase bachelor's degree attainment by one percentage point or less per $1,000, with most rigorously-evaluated aid programs increasing attainment by less than 0.5 percentage points per $1,000. By contrast, BL advising increases bachelor's degree attainment by over two percentage points per $1,000. If we instead focus on just the pre-college advising, the effect size grows to over four percentage points per $1,000. See Figure II.

A Recruitment and application process

BL actively promotes the Access program through information sessions and individual student meetings at high schools and by seeking referrals from non-profit partners that work with students earlier in their high school trajectory. Staff encourage high school juniors who are interested in the program to complete an application during the second half of junior year. 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.[11] For the high school graduating classes of 2015 and 2016, BL included language indicating that the program had limited capacity to serve qualified students, and would use a lottery to assign program invitations among qualified applicants.

B Access Program

BL advisors begin working with admitted students between the end of their junior year and the start of their senior year of high school. Students meet with their advisor for an hour every 3-4 weeks over the course of their senior year in high school. These meetings take place at BL's office in each community. During their meetings with students, BL advisors provide comprehensive college and financial aid support for students. During the fall of senior year, advisors work with students to explore and learn about colleges and universities that are a good match for their academic ability and interests, with a focus on guiding students towards colleges with a good combination of quality and affordability. Advisors then help students identify a set of reach, match, and safety schools to which they will

[11] An earlier regression discontinuity design evaluation of the BL program in the Boston area found suggestive evidence that BL positively impacts college enrollment (Castleman and Goodman 2018). The paper does not examine impacts on degree attainment, and the results are imprecisely estimated (including enrollment effects as small as negative 20 pp and as large as 40 percentage points); rely on a manipulable running variable; and are local to the 2.5 GPA threshold determining eligibility for the program.

apply and support students to complete applications for these schools. Advisors also help students to complete the Free Application for Federal Student Aid (FAFSA) and to apply for supplemental scholarships. Once students receive college acceptances and financial aid packages, BL advisors work with students to interpret their financial aid award letters and to select a college or university that aligns with a student's goals and circumstances.

Advisors work full time. All advisors have a college degree and 17 percent have a master's degree. Most advisors are female (75 percent) with roughly a quarter Black and a quarter Hispanic. The median advisor age is 26. Advisors have an average caseload of 50-60 students.

Nearly every student assigned to treatment (97 percent) had at least one interaction with an advisor between the beginning of the Access advising program (May of a student's Junior year of high school) and the transition period to college (August after a student's Senior year of high school). Over the 15-month period, advisors interacted with students an average of 13 times, with the majority of these interactions occurring as in-person meetings in the advisor's office. Advisors spend an average of 10 to 15 hours working directly with each student.[12]

C Success Program

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.[13] The target institutions are primarily moderately selective four-year colleges and universities, approximately two-thirds of which are public institutions. They were selected due to a combination of proximity to BL offices and significant prior enrollment of BL students. Campus-based advisors at each target institution meet regularly with students once they have matriculated in college; first-year students meet with advisors approximately three to four times per semester, while

[12]See Appendix Table A3 for statistics on the advisor-student relationship and Appendix Figure A14 for a visual representation of the frequency of student-advisor interactions over time. Data for this table and figure come from advisor:student interaction records maintained by Bottom Line.

[13]Appendix Table A1 shows the list of target institutions.

older students meet with an advisor twice a semester on average.[14] Success advisors provide a combination of academic support (e.g., course selection and making use of advising and tutoring services) and 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.

II 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. Among students who met the BL eligibility criteria (GPA of at least 2.5 and family income below 200 percent of the poverty line), 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. The first experimental cohort includes 1,429 students and the second experimental cohort includes 993 students, for a total experimental sample of 2,422 students.

A Data

Our data come from three primary sources: the intake application, a survey we conducted with students during the spring of their senior year in high school, and the National Student Clearinghouse. The intake 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

[14] Advisors adjust meeting frequency based on student need, meeting more regularly with students who are experiencing some form of challenge in college. Success advisors typically serve students across 2-3 different campuses, and work with 30-40 students per campus.

they applied for advising, 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 advising. The application also collected information on the set of institutions that students were interested in at the point of intake, providing a unique opportunity to observe the baseline college preferences of low-income students. Our spring of senior year survey asked students about their college applications; whether and when students applied for financial aid; whether students received assistance reviewing their financial aid award letters; and a series of questions about factors influencing students' decisions about whether and where to enroll in college. The National Student Clearinghouse (NSC) provides student by term-level college enrollment and degree attainment data, with coverage across more than 97 percent of college enrollments in the country.

B Baseline Equivalence

In Table 1, we report results from regressions of baseline characteristics on the treatment indicator and site-by-cohort fixed effects. Across 20 measures, we find 2 significant differences at the 5 percent level: treated students are slightly less likely to be citizens and somewhat more likely to have employed fathers (though this measure is missing for nearly half the sample). Omnibus tests confirm balance: we find no treatment effect on a predicted probability of bachelor's degree attainment derived from baseline measures, and an F-test of joint covariate effects is consistent with randomization. For completeness, we also present treatment effects on enrollment and degree attainment with and without covariates.

III Empirical Strategy and Results

We estimate the effects of an offer to participate in intensive advising on college enrollment, enrollment quality, persistence, and degree attainment. As the proportion assigned to treatment varied by site and cohort, we control 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 a post-secondary education 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 advising organization, whether sibling participated in BL). The l_{ij} are site by cohort fixed effects (i.e., risk set indicators), which 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.

A Enrollment

Table II contains our estimates of the impact of intensive advising on students' enrollment and enrollment quality. The point estimate in the first row of column 2 shows that assignment to treatment increases the likelihood of college enrollment by 5.3 percentage points (6.5 percent). As expected, given BL's emphasis on four-year enrollment, estimates in the second row of Table II indicate substantially larger effects on four-year enrollment, with a 9.1 percentage point increase; this is a 13 percent increase relative to four-year enrollment in the control group. As expected, given BL's emphasis on four-year enrollment, estimates in the third row indicate that a reduction in two-year enrollment (4 percentage points) contributed to the rise in four-year enrollment.

The remaining rows in Table II estimate the impact of intensive advising on the quality of institutions at which students enroll. Treated students are substantially more likely to attend institutions with higher graduation rates, lower default rates, higher post-enrollment earnings, and higher mobility among attendees.[15] For instance, treated students are 11 percentage points more likely to attend institutions with above-median earnings for graduates; this represents a 17 percent increase relative to the control mean. The estimates are essentially unchanged upon incorporation of covariates.

In Figure I we compare enrollment rates over time for the BL students compared to the control group. We measure enrollment each term (Fall or Spring) starting one year after high school and continuing through five years after high school. The top panel presents overall enrollment rates over time while the bottom panel presents enrollment rates over time at four-year institutions. Starting in the first Fall semester after high school, and continuing through the Spring semester four years after high school, BL students maintain a substantially higher rate (∼5 percentage points) of enrollment than control students (Panel A). We observe a more pronounced pattern of increased four-year enrollment over time, with BL students maintaining a higher rate of enrollment (∼10 percentage points) starting the first Fall after high school and continuing four years after high school (Panel B). In both cases, we observe virtually no difference in enrollment starting five years after high school as a sizeable share of students assigned to treatment earn bachelor's degrees and leave college.[16]

B Degree Attainment

In Table III we present estimates of intensive advising's impact on degree attainment. The point estimates in column 2 show that, starting four years after high school, intensive advising generates large increases in the share of students that earn a bachelor's degree. Treated students are 6.2 percentage points more likely to earn a bachelor's degree within four years after high school; this represents a 23 percent increase relative to the control group mean of 26.8 percent. By five years after high school, this grows to a 7.6 percentage point effect

[15] Specifically, we estimate effects on whether an individual is initially observed enrolled at a four-year institution with an above median 6-year graduation rate (53.8 percent), with a student loan default rate below the median (7 percent), with earnings above the median for all college enrollees ($35,800) in Chetty et al. (2017), and with "mobility" above the median college in Chetty et al. (2017).

[16] As we show in Appendix Figures A2 and A3, these patterns of overall and four-year enrollment over time are quite similar for both experimental cohorts.

relative to the control mean of 47.1 percent. By six years after high school (which we observe just for the first experimental cohort), the control mean bachelor's degree attainment rate rises to 52.8 percent, yet we see an even larger treatment effect (9.6 percentage points) on BA attainment.

The next four rows in Table III show that intensive advising's impacts on degree attainment result mainly from increasing the share of students who graduate from institutions with higher graduation rates, lower default rates, higher average earnings among their graduates, and higher mobility rates. The final two rows in Table III show that a moderate share of intensive advising's impact on bachelor's degree attainment likely results from diverting students who would otherwise have attended two-year institutions and received associate's degrees to instead enroll at four-year institutions and complete their bachelor's degree. For instance, BL students were 3.0 percentage points less likely to earn an associate's degree within five years. The estimates are nearly identical upon controlling for baseline covariates.

In Appendix Figure A4, we explore the extent of heterogeneity in bachelor's degree effects across common subgroups defined by race, gender, high school performance, access to alternative college access programs, and family resources. We see some suggestive evidence of smaller treatment effects for those with below-median high school GPAs in Panel A, but this difference appears to be driven by low levels of degree attainment in this group four years after high-school graduation. Looking five years after high-school graduation, BL's positive impacts on bachelor's degree attainment are quite consistent across student groups.

IV Mechanisms

What explains the large impact of this advising model on degree attainment? In this section, we use multiple approaches to argue that improving college quality is the primary channel through which advising affects bachelor's degree attainment. To implement these approaches, we need a measure of initial college quality for the entire experimental sample; we refer to this as the adjusted graduation rate. For enrolled students, we construct this measure equal to the 2015 graduation rate for the school the student was enrolled in the fall after their senior year of high school.[17] For students who were not observed enrolled in the fall after their senior year, we cannot assign a school-specific graduation rate. Instead, we estimate the 6-year bachelor's degree attainment rate of students in the control group who were unenrolled in the fall after their senior year but who subsequently enrolled and completed a bachelor's degree, and assign that number as the adjusted graduation rate for all unenrolled individuals.

As a brief overview of our approach, we first capitalize on access to unique data on baseline college preferences to argue that, in the absence of intensive advising, many low-income students appear to make suboptimal choices about which colleges to explore. We show that it is these students in particular whose college choice appears to respond most to the availability of advising, and for whom greater improvements in initial college quality are followed by greater increases in the likelihood of degree attainment. Second, we use causal forests to show that heterogeneity in experimentally induced changes in college quality is strongly correlated with heterogeneity in changes in bachelor's degree attainment. We incorporate our data-driven measures of treatment heterogeneity on college quality into a mediation analysis, which lends further support for the important role of college quality in mediating bachelor's degree attainment. We conclude the section with a deeper exploration, leveraging student survey responses, of how intensive advising may affect students' college application and enrollment decisions.

A Using Baseline College Preferences to Understand College Choice

While Appendix Figure A1 provides some indication that many low-income students end up at institutions with poor combinations of cost and quality, it is not clear the extent to which these enrollment outcomes result from student baseline preferences (e.g. to attend institutions closer to home) versus other constraints such as admissibility or cost. Our

[17] We use graduation rates within 150 percent of normal time.

data allow us to better understand the role that baseline student preferences play in college choices. As part of their application to BL at the end of their junior year of high school and prior to randomization, all sample subjects were asked to list the set of institutions that they were interested in attending. We first use these data to document that many low-income students are interested in colleges that appear to be "suboptimal" based on measures of cost and quality and then demonstrate that the college choices and degree attainment outcomes of the least informed individuals improve the most with intensive advising. We use multiple measures to define whether a student has "suboptimal" baseline preferences.[18] Because this process is somewhat subjective, we consider a broad set of measures and show in our analysis below that treatment heterogeneity by baseline preferences is robust to the selection of specific measures.

Our first set of measures capture whether a student lists any suboptimal institutions, including a student indicating a baseline interest in a school with a below-median six-year graduation rate; a school with low graduation rate and net price roughly at or above the median in the national distribution (over $10,000); a school that has a bottom quartile graduation rate conditional on a student's GPA and predicted SAT; or a school with median earnings for individuals from low-income families ($0-$30,000) below the bottom quartile in MA or NY.[19] We also incorporate readily available proxies, flagging any institution that Barron's terms "Less Competitive", "Noncompetitive", or "Special" and any for-profit institution as "suboptimal" for our sample.[20] Depending on the measure, between a third and

[18]Specifically, we had one member of the research team create an extensive set of potential proxies for suboptimal preferences (developed in consultation with AI tools) and then had a second team member rule out the proxies that he felt did not necessarily reflect a mistake. This intersection approach resulted in the exclusion of potential measures such as high levels of within student variance in the size (i.e., undergraduate enrollment) of listed institutions, selecting only out of state colleges, or listing only a single institution. We also excluded one measure on which both team members agreed (high default rate) because almost no students listed an institution with a high default rate.

[19]SAT is predicted by regressing available SAT scores on available GPA, MCAS math, MCAS verbal, Regents Math, and Regents Verbal scores. We use the earnings measures from MA and NY institutions because these areas have higher earnings than elsewhere in the country.

[20]These institutions have limited or no admissions selectivity and tend to have low graduation rates. Given the GPA cutoff required by BL (2.5), all sample students meet the baseline requirements to attend more selective institutions.

two-thirds of low-income students express interest in a "suboptimal" college. Over 40 percent list a college with a low graduation rate and a high net price and nearly two-thirds list a school with a bottom quartile graduation rate given their academic performance (Appendix Table D1).

In addition to the measures above, which capture whether students include *any* suboptimal institutions in their baseline preferences, we also consider measures that aggregate information from the full set of institutions that individuals list, including the share of schools listed with low graduation rates; low graduation rates and high prices; bottom quartile graduation rates given academic performance; and poor earnings outcomes, as well as whether a student lists any "match" institution (i.e., an institution for which their predicted SAT score falls between the 25th and 75th percentile of scores at the institution). Finally, we consider a continuous measure of suboptimal preferences based on the extent to which students list schools with lower than expected graduation rates given their academic background. This measure combines information on the number of potential mistakes (i.e., the share of institutions listed with residuals below zero) and the extent of those mistakes (i.e., the magnitude of the negative residual).[21] Summary statistics from these measures further support the notion that many low-income students are interested in colleges that appear to be "suboptimal" based on measures of cost and quality.

Given the prevalence of suboptimal baseline preferences, an important question is whether targeted advising can influence these initial preferences and improve long-term educational outcomes. To investigate this idea further, we incorporate the 12 proxies into an index that quantifies the intensity of suboptimal baseline college preferences, and then interact that index with treatment. We use two approaches to index construction. In our first approach,

[21] To be more specific, this measure regresses the graduation rates of institutions listed on verified GPAs and predicted SAT scores. We then obtain the residuals from that regression, which reflect the extent to which a listed institution has a graduation rate that is below or above other students with similar GPAs and predicted SAT scores. Since listing institutions with higher-than-expected graduation rates is not necessarily a mistake, we set positive residuals to zero. This avoids the ambiguity of distinguishing between a 'goodâ and 'very goodâ choice, focusing instead on suboptimal choices. We then take the average of residuals for each student across listed institutions.

we focus our analysis on an equally weighted index similar to that used by Kling, Liebman, and Katz (2007). This approach is simple and transparent.[22] However, it does not take into account the correlation of measures. If some of the measures are highly correlated, it is *possible* that the equally weighted index is in some sense double-counting the same information (and underweighting other information). To account for this potential double-counting, we consider a second index that weights each standardized measure by the inverse covariance matrix (Anderson 2008). We demonstrate robustness to other aggregation approaches in Appendix D.[23]

In Table IV, we show that the effects of advising on measures of degree receipt are significantly larger for those who appear to be less informed at baseline. For instance, a one standard deviation increase in suboptimal baseline preferences corresponds to a 3 to 4 percentage point larger effect of intensive advising on degree attainment, roughly half the magnitude of the average treatment effect. The larger increases in degree receipt are preceded by similarly sized increases in the quality of initial enrollment (i.e., four-year enrollment and adjusted graduation rate), supporting the notion that the effects on bachelor's attainment are causally mediated by improvements in school choice.[24] The interaction effect estimates using the inverse-covariance weighted index are somewhat smaller than the equally weighted index, suggesting that highly correlated measures (e.g., listing a low graduation rate school and listing a school with a low graduation rate relative to similar students) interact more

[22]The index is generated by first standardizing each component measure to have a mean of zero and a standard deviation of one, averaging them, and then re-standardizing.

[23]In the appendix, we describe the other approaches we explored (e.g., the use of principal component analysis (PCA) and factor analysis to generate indices); discuss tradeoffs between these approaches; and present results from using each index to explore treatment heterogeneity by baseline preferences.

[24]The interaction effects on four-year enrollment are significant across index measures. While the coefficients for the adjusted grad rate are not significant at conventional levels, the positive direction of the coefficient further suggests that improvements in school choice are a key mechanism. We show that our conclusions are largely robust to the measures included in both indices. Appendix Figures D1 and D2 contain the distribution of interaction effect estimates generated when dropping any three measures. For the four-year enrollment and BA within five years outcomes, the interaction effect estimates are fairly tightly clustered around the effects reported in Table 4; this is also true for the adjusted graduation rate outcome with the equally weighted index. The interaction effect estimates for the adjusted graduation rate with the inverse-covariance weighted index are somewhat more dispersed, with a minority of estimates suggesting very small (less than 0.5 percentage points) negative interaction effects.

strongly with treatment.

B Explaining Bachelor's Treatment Effects Using Causal Forests

We have shown in the prior sections that participation in intensive college advising generates large increases in the share of low-income students that attend higher-quality institutions. Our argument is that shifting students to attend higher-quality institutions results in the higher rates of degree attainment that we observe. But we also acknowledge the possibility that the students induced to attend higher-quality colleges and universities may have been inframarginal to bachelor's degree attainment and that advising is affecting degree completion among a different population of students.

One traditional approach to distinguishing these explanations is to examine patterns of subgroup heterogeneity to see if the subgroups with larger treatment effects on initial enrollment quality are also the subgroups with larger treatment effects on bachelor's degree attainment.[25] Recently developed causal forest methods provide a much more highly-powered way to explore treatment effect heterogeneity than traditional approaches for heterogeneity analysis; we use these methods to explore relationships between treatment heterogeneity in mediators (e.g. enrollment quality) and treatment heterogeneity in ultimate outcomes (e.g. degree attainment) (Athey and Imbens 2016; Athey and Wager 2019).[26]

To investigate whether advising's impacts on enrollment quality are a primary driver of higher rates of degree attainment, we estimate separate personalized treatment effects (PTEs) for two outcomes: (1) the adjusted graduation rate, and (2) bachelor's degree attainment within five years. The PTES are highly predictive of treatment effect heterogeneity. For example, regression analysis shows a strong relationship between (1) the interaction of

[25]For example, if Black students experienced minimal effects on initial enrollment quality but large effects on bachelor's degree attainment, it would suggest that initial enrollment quality is unlikely to be an important channel through which the effects are operating. In contrast, if we saw that Black students experienced large effects on initial enrollment quality and bachelor's degree attainment whereas non-Black students experienced minimal effects on both, it would *suggest* an important role for initial enrollment quality in mediating the effects of advising on degree attainment.

[26]In Appendix B we describe causal forest methods, how they differ from traditional approaches to heterogeneity analysis, and details of our approach in greater detail.

PTEs for adjusted graduation rates and treatment, and (2) actual adjusted graduation rates of initial school choices, with a first-stage partial F-statistic of over 300 (versus around 1 for the simple interaction of baseline covariates with treatment). In Figure A5, we display the relationship between the PTEs we estimate for attendance at higher-quality institutions (X axis) and the PTEs we estimate for bachelor's degree attainment (Y axis). We observe a positive relationship between the PTEs: students for whom advising has the largest positive personalized treatment effects on enrollment quality tend to be the same students for whom advising has the largest PTEs on bachelor's degree attainment; the signal correlation of this relationship is 0.35.[27] In other words, assignment to advising appears to increase degree attainment more for students for whom assignment to advising shifts their college choice to higher-quality institutions.

How much of the overall treatment effect on degree attainment is accounted for via increases in the quality of initial college enrollment? We can incorporate the PTEs from our causal forest approach into a more formal mediation analysis.[28] To overcome the endogeneity of school choice, we use the interaction of PTEs and treatment to instrument for observed enrollment quality.[29] This approach overcomes concerns about the role of "pre-treatment confounders" (e.g., greater aptitude or academic preparation) in a standard mediation approach, but there may still be other mediators that are shifted by treatment in a similar way as initial enrollment quality (i.e., post-treatment confounders). We proceed with that caveat in mind.

Table V compares the results from this exercise with those from a standard mediation

[27]Appendix Figure A11 shows a similar relationship between the individual PTEs for attending a high-graduation rate college (X axis) and the individual PTEs we estimate for bachelor's degree attainment (Y axis). Appendix Figure A12 show a similar but weaker relationship between the individual PTEs we estimate for attendance at a four-year institution (X axis) and the individual PTEs we estimate for bachelor's degree attainment (Y axis).

[28]We provide a more complete and formal discussion of the assumptions of mediation analysis and the potential advantages of our approach in Appendix C.

[29]Interacting treatment with baseline covariates would similarly overcome some endogeneity concerns, but this simpler approach produces a partial F-statistic around 1 when using the full set of baseline covariates presented in Table 1; as we show earlier the interaction of PTEs and treatment produces a first-stage partial F-statistic of 316.

analysis. The instrumented effect of shifts in *initial enrollment quality* is similar, but smaller, than the relationship observed using the standard mediation analysis approach (0.93 vs 1.02). Using this simple approach, shifts in the quality of initial enrollment explain roughly 72 percent of the overall treatment effect, confirming the important role of college quality in mediating bachelor's degree attainment.

We can also incorporate shifts into *target institutions* into our mediation analysis approach to more formally disentangle the contribution of the two factors. To do so we use the interaction of treatment assignment with the PTE for attending a target institution as a second instrument. When we incorporate both instruments into the mediation approach simultaneously, we see that initial enrollment quality continues to generate a significant increase in degree attainment. The implied role of college quality in explaining degree attainment (0.89) is similar to the estimate produced when instrumenting solely for initial enrollment college quality (0.93). In contrast, attending a target institution does not generate a significant increase in degree attainment, although the point estimate is non-trivial in magnitude.[30]

C Exploring Advisors' Influence

How do advisors influence students? There are several channels through which advisors could shape students' behavior and outcomes. They could support students to explore and apply to a broader range of colleges and universities, including higher-quality options. Alternatively, their influence could arise from working with students to strengthen the applications they submit, or by helping students apply for financial aid and scholarships to pay for college. Advisors could also support students to make informed choices about where to enroll among

[30] If we take the point estimate (0.062) in column 4 of Table V at face value, it implies that attending a BL target institution increases the likelihood of degree attainment by 6.2 percentage points *for those experimentally induced into target institutions by advising.* Given the treatment effect on attendance at a target institution (10 percentage points from Table II), this implies that advising may have increased degree attainment by 0.6 percentage points through this channel. This is roughly 8 percent of the overall treatment effect. There is similarly little evidence that the ongoing in-college advising benefited inframarginal students. We discuss this at greater length in Appendix C.

their accepted choice set. In the final results sections, we leverage survey data to explore where in the application process advisors have influence on students. 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 advisor). The survey also included a free-form response for students to comment on their "college decisions or the application process as a whole." Approximately 56 percent of students responded to the survey, with roughly equal response rates among treatment and control group students.[31] Given the focus on the first cohort and the incomplete response rates, we present the associated findings as exploratory.

In Panel A of (Table VI) we present data on the completion of college and financial aid milestones. This evidence suggests advisors' influence on enrollment choices likely occurred during the college search and application phase and again during the college choice phase. Advising had no impact on *whether* students applied to college, with nearly all of the experimental sample (99 percent) reporting they applied to college. Treated students, however, reported submitting nearly three additional applications, suggesting advisors may have supported students to expand their potential choice set. We observe no evidence that advising affected students by increasing the rate at which they applied for financial aid or scholarships, or the share that received aid.[32] Nor does it appear that BL had a substantial influence on whether students were accepted to the colleges to which they applied. Treated students were, however, substantially more likely to report engaging with someone to review

[31]The response rate for the control group was 0.558, with a 0.016 (se 0.029) coefficient on a treatment indicator variable, controlling for site by cohort indicators. Appendix Table A4 suggests little selection or differential selection into survey response. As seen in the table, observables of respondents are similar to those of the full sample. Similarly, the characteristics of treated respondents are broadly similar to control respondents.

[32]Across the experimental sample nearly all students completed the FAFSA (97 percent); over half reported applying for scholarships, and nearly three-quarters reported receiving an offer of financial aid from a college. There are no significant differences between treated and control students across these measures.

and discuss their award letters (84 percent vs. 67 percent for the control).

Our qualitative analyses of free-form comments students provided about their "college decisions or the application process as a whole" suggest that advisors were effective during these application phases by providing students assistance navigating complex choices (e.g., where to apply or where to enroll among accepted options) and thereby reducing the difficulty and stress of the overall process.[33] Using natural language processing and human coding, we evaluated the effect of advising on the sentiment and topics associated with each student response, which we present in Panel B of Table VI. Treated students were nearly 30 percentage points more likely to express positive sentiment or gratitude in their responses, more than double the rate in the control group. Consistent with the challenges that intensive advising was designed to solve, nearly half of control group students mention something about the difficulty of the college application process. Advised students were 26 percent less likely to discuss having difficulty with the application process and were substantially less likely to describe the application process in negative terms or mention a lack of support.[34]

Selected quotes from the free-form responses support these findings. For example, one treated student said that the "process was tedious, often confusing and very redundant. [I] feel like high school administrations can do more to prepare students for college search. Bottom Line was my primary tool for completing college applications and I am very grateful to have a bottom line counselor." A control student noted "it was a very difficult process for me because I am the first one to go to college in my family and I did not get help from them because they do not have the knowledge of it", while another noted "there should be more programs to help much more students with the college application process because it can be stressful and confusing." These qualitative patterns of advisors providing emotional support and assistance with the search and decision process are consistent with important

[33]We present these exploratory findings with the caveat that only 230 individuals responded to this free-form question. While there are minimal differences in the baseline observables of treatment and control respondents, there are some measurable differences between those who provided a free form response and those who did not.

[34]The exact magnitudes of the means and treatment effects differ slightly based on how we use the human or NLP coding. Full results and coding methods are presented in Appendix E.

channels noted in more extensive qualitative analyses of the effects of advising in a different context (Bergman et al. 2024).

While advised students were less likely to report a lack of assistance with the college application process, one interesting finding from our qualitative analysis is that few students in either experimental group (sixteen percent of the control group; less than two percent of the treatment group) reported lacking assistance. One channel through which intensive advising may have influenced students, though, is by leading students to substitute trained college advisors for other, potentially less informed, sources of advice. A student quote supports this potential substitution effect: "It would have been a great opportunity to work with them [advisors] especially since I didn't have anybody to realy help me with whole process since I am a first generation college student." In Appendix Table A6 we present the share of students in the experimental sample who reported discussing important college topics with different sources of advice they rated as "somewhat or very important" in their college application and decision process. Topics included which colleges to apply to, how to apply for aid, and which college to enroll at, among others, while sources of important support included parents, other family, guidance counselors, teachers, friends, and BL advisors (treatment only). Of note is that roughly 90 percent of treated students received advice from BL advisors on each topic, higher than any other source of advice on any topic. Turning to estimates of differences between treated and control students on guidance from other sources, we observe some direct evidence of substitution. The estimates are imprecise so we interpret these patterns cautiously. That being said, we observe a consistent directional pattern of BL students being *less* likely than control students to discuss nearly all topics with other sources of support. This modest evidence of substitution in *whether* a student has discussed a topic with other sources of support suggests there may have been even more meaningful substitution towards more informed sources of advice as students navigated complex choices, such as where to apply or enroll.

V Cost Effectiveness and Scalability

The effects of intensive advising on bachelor's degree attainment appear to be as large or larger than any intervention for which researchers have rigorously estimated treatment effects. But at what cost? In this section, we calculate the cost effectiveness of intensive advising and compare it to other strategies that have increased bachelor's degree attainment rates among lower-income populations. We show that intensive advising appears more cost effective than other rigorously evaluated strategies to increase bachelor's degree attainment (Figure II). We then discuss evidence that suggests the intensive advising model is likely scalable.

A Cost Effectiveness

We consider two potential measures of BL program costs. First, given evidence in the prior section that pre-college advising is largely responsible for the effects on bachelor's degree attainment, we use the estimated cost per student of the Access advising program ($2,256) scaled by a conservative measure of the take up rate of 0.95 (i.e., any student who had at least one office visit), amounting to $2,145 per student. This cost incorporates both the direct cost of administering the program (i.e., advisor salaries) as well as administrative (i.e., overhead) costs.[35] Second, we use the estimated full cost of the program, including the initial Access advising as well as the ongoing in-college Success advising. This amounts to $2,016 per offered student for the Success program and $4,161 total per student offered both Access and Success advising.[36]

A natural question is whether advising is a more cost-effective strategy to increasing degree attainment than other options. For example, while the 6-year bachelor's attainment

[35]All figures provided by Bottom Line. In recent years, roughly 73% of this cost comes from salaries; 18% come from office expenses (e.g. rent); and 9% come from costs to support the national BL team and organization-wide training and professional development. All dollar values adjusted to 2016 dollars.

[36]To calculate the total program cost we add the cost of the Access advising program to the expected cost of the Success program. Because only 43 percent of treated students end up at target institutions (and thus would have been offered Success advising), we conservatively assume that 40 percent will take up Success advising for a total of four years.

effects generated by advising are similar in size to those estimated in a recent experimental evaluation of Buffett Scholars, a program that provides merit-based aid for low-income students, the Buffett program cost per treated applicant is over *eight times* the total amount spent per BL-offered student, and roughly *eighteen times* the cost of the pre-college advising. In Figure II, we show that intensive advising appears more cost effective than all financial aid programs for which we could find rigorous estimates of impacts on bachelor's degree attainment.[37] Intensive advising similarly seems more cost effective at increasing degree attainment than other prominent interventions (e.g., early childhood education, reduced class size, or school spending) for which there are reported effects on degree attainment, although it is important to note that these interventions were not targeted at improving post-secondary outcomes. Indeed, intensive advising appears more cost effective at increasing bachelor's degree attainment than any rigorously evaluated program we were able to find in the literature.[38]

An important note about our cost calculations is that our reported program costs do not include any potential downstream increase in costs resulting from changes in students' postsecondary behavior. In particular, it is possible that the shifting of students into higher quality institutions coincides with higher costs. While shifts in enrollment make it difficult to estimate this directly, there is no evidence that treated students are paying higher average net prices, though we do find some evidence that students are attending institutions with

[37]Most programs report bachelor's degree impacts 6 years after the expected year of high-school graduation. While our 6-year impact estimates are larger than our 5-year estimates, we focus our presentation on the more conservative 5-year bachelor's degree estimates. We exclude evaluations with state data only as these estimates reflect some shifting to in-state institutions.

[38]We include in Figure II all studies published in top general interest or field journals since 2009 that evaluated U.S. interventions from the last 50 years; contained estimated treatment effects on bachelor's degree attainment; and included cost measures (details contained in the note to Appendix Table A7). There are additional unpublished follow-up reports evaluating low-cost interventions (e.g., personalized assistance to apply for federal financial aid (https://data.nber.org/data-appendix/w15361/w15361.addendum.pdf); interactive text messaging and peer mentoring with pre-matriculation tasks during the summer after high-school (https://osf.io/m29pv)) that either estimate non-significant effects on degree attainment or that do not report cost estimates. While these studies are not powered to detect small effects on degree attainment, the low costs of these interventions suggest they could still be cost-effective. However, their total impacts on BA attainment are likely modest.

higher sticker prices and somewhat higher instructional expenditures.[39] In other words, treated students' costs are not increasing, although the institutions they are attending are giving them somewhat larger price breaks. Who ultimately bears the costs of these modest price breaks is unclear, but there is no apparent increase in costs for the advised students or the program.

B Scalability

While the cost effectiveness of intensive advising in increasing degree attainment appears unmatched, maintaining implementation quality at scale may be more challenging than for other programs, like financial aid, that may be more straightforward to administer across different contexts and populations. We evaluate the potential scalability of Bottom Line's (BL) intensive advising model across several dimensions: (1) expanding to different student populations, (2) maintaining program quality with a broader pool of advisors, (3) expanding to additional geographic locations, and (4) potential supply constraints at higher-quality colleges and universities. Below, we discuss each margin in turn and present evidence supporting the model's scalability.

B.1 Expanding to Different Student Populations

As discussed previously, we observe little evidence of heterogeneity in effects across student types, implying the potential of intensive advising to be effective in markets with different student or family compositions. A related question pertains to the breadth of its reach in the markets where it has operated to date; if BL is only able to recruit a small share of eligible students in the cities where it locates, it could be expensive or inefficient to expand to numerous additional sites. But in its focal cities, BL serves a sizeable share (60-70 percent) of

[39] The net prices of institutions attended by treated students are insignificantly different from those attended by control students (coef 376, se 324) whereas sticker prices and instructional expenditures are around \$1,700 and \$800 higher, respectively.

the students that meet program eligibility requirements.[40] The high rate of take up suggests that were BL to scale, it would likely reach most eligible students in small/medium cities. Another important consideration is whether the effects are likely to be similar if the program was expanded to additional individuals who are less likely to apply (e.g., outside of the 60-70 percent in the Boston area). While we cannot answer this question definitively, we think it is likely intensive advising would maintain efficacy with a broader population of students. Our estimated treatment effects are generated off of cohorts of applicants for which BL aggressively recruited students to meet sample size targets for the experiment; these sample sizes were substantially larger than the number of students served in prior cohorts. In some sense then, the estimated average treatment effects incorporate the treatment effects for individuals who would not have applied absent the experiment.

B.2 Maintaining Program Quality with a Broader Pool of Advisors

It is also noteworthy how consistent advisors are at improving student outcomes.[41] Indeed, as shown in Figure II, even the bottom two-thirds of advisors are more cost-effective in increasing degree attainment than alternative options. From a scalability perspective this is 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 advisors who may be hard to identify and recruit in other contexts.

[40]Bottom Line internal estimate obtained by working with a Massachusetts consulting firm. While BL was not operating in New York at the time of the market analysis, the firm's estimates suggest that BL's reach in New York only serves a small share of the students in the city who meet the program eligibility requirements.

[41]See Appendix Figures A15 and A16 and Appendix F for a more complete discussion of the consistency of effects across advisors. F-tests of the equivalence of advisor fixed effects fail to reject the null of equivalent effects.

B.3 Expanding to Additional Geographic Locations

Another important question is whether the effectiveness of the program can be maintained when expanding to a new market, as well as how long it may take to ramp up the program in new locations. A longer period of program maturation would delay the organization's ability to scale its impact. The New York site had been in operation for only a few years prior to the RCT. Large positive effects of the advising model there provide direct evidence of scalability and suggest that the program reaches maturity and efficacy quite rapidly (Figure II).[42] The consistency of impacts across multiple program sites operating in different states, each under local program leadership, suggests the potential for intensive advising to maintain effectiveness when scaled. It is further impressive that intensive advising has generated such large impacts on students' postsecondary outcomes in these markets given the saturation of these markets with college assistance organizations (44 percent of students reported that they were working with a different college access organization at the time they applied to BL). The impacts of intensive advising could be even larger if applied in communities where students have little or no existing access to alternative college advising supports.

Of course, it is possible that the effects of intensive advising are stronger in the Boston and New York area than they would be in other locations. For instance, Allcott (2015) finds that the ATE in an energy conservation experiment implemented across more than 100 sites was 71 percent of what would have been predicted by impact estimates from initial RCT sites. While it is not clear that a similar pattern would be observed in our context, even applying this reduction in program efficacy at scale, intensive advising would still be more cost effective than all other programs we present in Figure II.

[42]The increase in bachelor's degree attainment after five years in the Boston area is 7.4 percentage points, and 7.2 percentage points in New York City. The Boston area includes the Boston and Worcester sites. The latter is much smaller (337 students) so for precision we combine with the Boston site. However, impacts on BA within five years are very similar for the Boston (7.2 pp) and the Worcester sites (7.4 pp).

B.4 Potential Supply Constraints at Higher-quality Colleges and Universities

Assuming for the moment that BL could maintain implementation quality with substantial expansion, the efficacy of the model could still be constrained if the supply of available "seats" at high-quality institutions is too inelastic. However, using our measure of high-quality, these institutions account for a substantial (59%) and responsive share of enrollment, suggesting that intensive advising is not just crowding out other students.[43] Were the program to be scaled up, supply constraints are unlikely to meaningfully limit the effectiveness of intensive advising in increasing degree attainment.

VI Conclusion

Through a multi-cohort, multi-site RCT, we provide robust evidence that intensive advising generates large increases in degree attainment among low-income students. We use unique baseline data on school interests and casual forest methods to demonstrate that intensive advising's impact on attainment is generated primarily by shifting students to enroll at higher-quality institutions. These findings highlight the important role college quality plays in improving degree completion rates.

Analyses of survey data suggest that advisors facilitate improved college choice via a combination of emotional support and streamlining of the college search and decision processes. These complementary functions of guidance and support appear integral to helping students to navigate a complex set of choices about where to apply and enroll.

The consistency of our results across sites, cohorts, advisors, and students indicates that intensive advising may provide a scalable solution to improving postsecondary educational attainment and, potentially, economic mobility for low-income students. Providing cities with a combination of financial and technical assistance to replicate the model could be a

[43] Between 2001 and 2015, enrollment at these institutions rose over 23 percent. These institutions also appear to increase capacity in response to demand; regressing log enrollment on log applications in first differences indicates that enrollment rises by 4.4 percent for every 10 percent increase in applications. Based on authors' calculations using IPEDS data from 2001 through 2019.

more efficient approach to increasing bachelor's degree attainment than offering students additional aid. Indeed, providing intensive advising to every eligible high-school student (roughly 34 percent meet the eligibility requirements) would cost \$2.7 billion, roughly 10 percent of the cost of doubling the Pell grant.[44] More generally, strategies that improve the quality of the colleges attended by low-income students, such as intensive advising, likely have the most potential to improve degree attainment.

[44]Authors' calculations using NCES Powerstats and the High School Longitudinal Study (HSLS) of 2009 multiplied by the cost of pre-college intensive advising.

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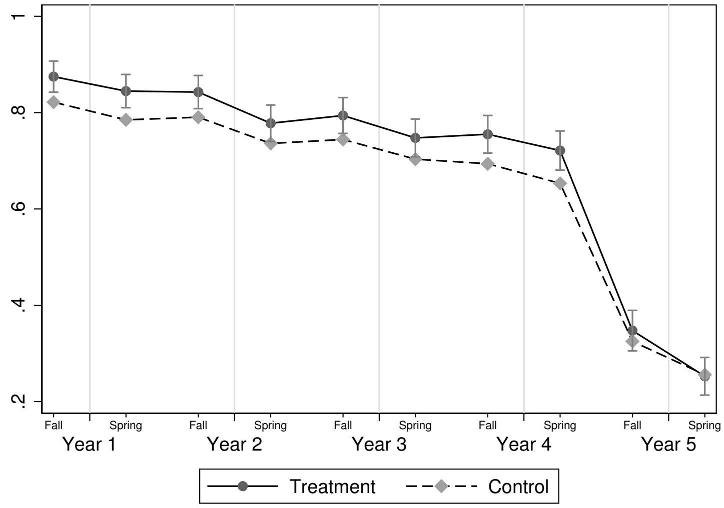
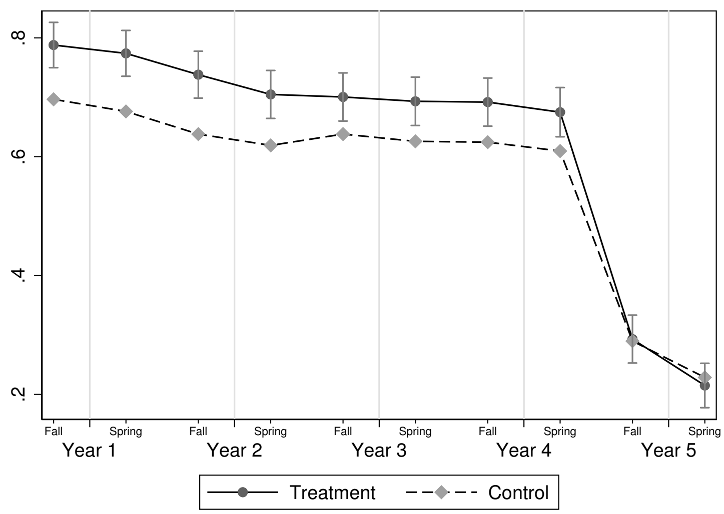
Figure I: College Enrollment Over Time



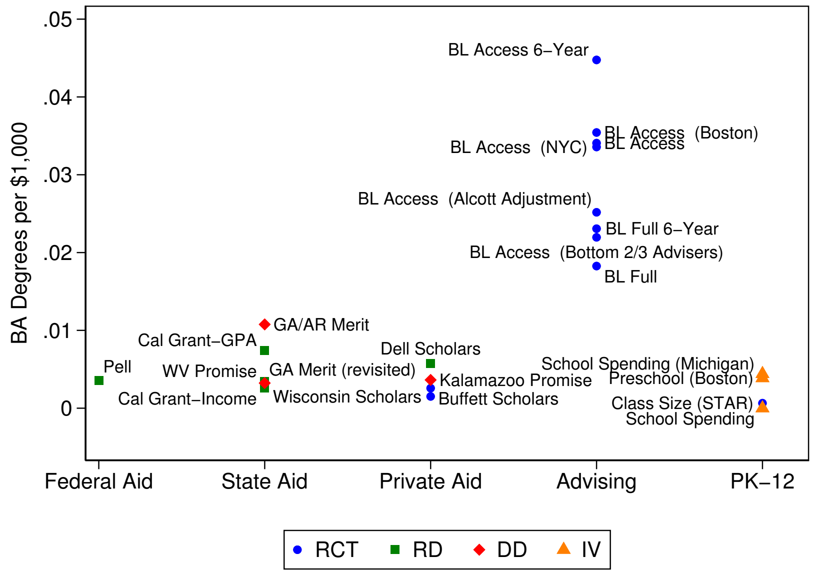
(a) Enrolled



(b) Enrolled Four-Year

Note: Figure illustrates the share of control and treated students enrolled in college in each semester. Year 1 is the academic year beginning in the fall after each high school class's senior year in high school. Treatment line points add estimated treatment effect from equation (1) to the control means. A student is considered enrolled in the fall if enrollment begins after June but by October and lasts at least 30 days. A student is considered enrolled in the spring if enrollment begins after November but by February and lasts at least 30 days. Panel B restricts this variable to enrollment in four-year institutions. Statistics derived from BL and NSC data.

Figure II: Bachelor's Degrees Generated per $1,000 of Direct Cost



Note: Effect sizes produced by dividing the reported estimate of the effect of a program on bachelor's degree attainment by the corresponding cost (inflated to 2016 dollars). BL Access effect sizes scale by the cost of the pre-college advising program. BL Full effect sizes scale by the total cost of the intensive advising program. Effect sizes for the bottom 2/3 of advisors uses the precision-weighted average of effects for the bottom 2/3 of advisers estimated using adviser fixed effects. The Alcott adjustment scales the estimated treatment effect by 0.71, the ratio of the scaled nationwide average treatment effect to that implied from the initial pilot studies (Allcott 2015). BL estimates are for bachelor's degree attainment within 5 years of high-school graduation unless otherwise noted. BL 6-year estimates rely on the first cohort only. Most other studies report 6-year or ever BA estimates. See Appendix Table A7 for additional information.

Table I: Descriptive Statistics and Randomization Tests

	Control Mean (1)	Treatment (2)
Female	0.697	-0.004
		(0.021)
Black	0.302	0.022
		(0.021)
Hispanic	0.325	-0.008
		(0.021)
Asian	0.246	-0.009
		(0.020)
Other Race	0.094	0.001
		(0.014)
Citizen	0.787	-0.039**
		(0.019)
Verified GPA	3.264	-0.004
		(0.027)
Parent AGI	22520	394
		(840)
Household Size	4.26	-0.003
		(0.074)
Mom Employed	0.641	0.005
		(0.023)
Mom Employed (missing)	0.144	-0.007
		(0.016)
Dad Employed	0.435	0.053**
		(.024)
Dad Employed (missing)	0.446	-0.004
		(.023)
First Generation	0.811	0.000
		(.019)
Sibling College	0.389	-0.004
		(.023)
Sibling College (missing)	0.059	-0.011
		(.010)
Sibling Bottom Line	0.075	0.001
		(.013)
Sibling Bottom Line (missing)	0.074	-0.001
		(0.012)
Other Program	0.444	-0.009
		(.022)
Prob (BA Degree in 5 Years)	0.492	0.003
		(0.008)
Prob>F		0.546
Observations		2422

Note: Table provides summary statistics and tests of balance for the experimental sample. Column 1 contains control group means. Each cell in column 2 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. Prob(BA Degree in 5 Years) is estimated within the control using the full set of covariates and provides an omnibus test of balance. P-value from an F-test on the joint significance of baseline covariates in predicting treatment assignment. Robust standard errors in parenthe-

Table II: Effects on Enrollment in College

	Control Mean (1)	Treatment (2)	Treatment (3)
Any College	0.822	0.053***	0.0556***
		(0.017)	(0.017)
4-Year College	0.697	0.0914***	0.0951***
		(0.020)	(0.020)
2-Year College	0.128	-0.040***	-0.0408***
		(0.014)	(0.015)
High Grad Rate	0.291	0.093***	0.091***
		(0.020)	(0.021)
Low Default	0.291	0.072***	0.069***
		(0.020)	(0.021)
High Earnings	0.631	0.110***	0.113***
		(0.020)	(0.021)
High Mobility	0.608	0.103***	0.105***
		(0.020)	(0.022)
BL Target College	0.327	0.101***	0.105***
		(0.022)	(0.022)
Covariates		Yes	No
Observations		2422	2422

Note: Table provides estimated treatment effects on various enrollment outcomes for the fall after an individual's expected senior year of high-school. Enrollment outcomes defined as initial enrollment at an institution with an above median graduation rate (53.8), with a low student loan default rate below the median (7 percent), with earnings above the median for all college enrollees ($35,800) in Chetty et al. (2017), and with "mobility" above the median college in Chetty et al. (2017). BL Target institutions, those with available in-college Success advising, are listed in Appendix Table A1 and further discussed in the text. Column 1 contains control group means. Each cell in column 2 contains a coefficient from a separate regression of each outcome variable (indicated by the row title) on a treatment indicator variable, controlling for site by cohort (i.e., risk set) indicators as well as the covariates indicated in Table 1. Each cell in column 3 contains analogous estimates without controlling for covariates. Robust standard errors in parentheses. * ($p<0.10$) **($p<0.05$), ***($p<0.01$).

Table III: Effects on Degree Attainment

	Control Mean (1)	Treatment (2)	Treatment (3)
BA Degree (4 Years)	0.268	0.062***	0.059***
		(0.020)	(0.021)
BA Degree (5 Years)	0.471	0.076***	0.076***
		(0.022)	(0.023)
BA Degree (6 Years)[a]	0.528	0.096***	0.097***
		(0.027)	(0.029)
High Grad Rate BA	0.252	0.082***	0.081***
		(0.0189)	(0.020)
Low Default BA	0.254	0.066***	0.065***
		(0.019)	(0.020)
High Earnings BA	0.471	0.089***	0.091***
		(0.021)	(0.023)
High Mobility BA	0.456	0.088***	0.090***
		(0.021)	(0.023)
AA Degree (4 Years)	0.106	-0.033**	-0.030**
		(.013)	(0.013)
AA Degree (5 Years)	0.128	-0.030**	-0.026*
		(0.014)	(0.014)
Covariates		Yes	No
Observations		2422	2422

Note: Table provides estimated treatment effects on various degree attainment outcomes. Measures defined analogously as in Table 2, but for bachelor's degree attainment instead of enrollment. Unless otherwise indicated, bachelor's degree attainment is measured within 5 years of July 1 after an individual's senior year of high school. Column 1 contains control group means. Each cell in column 2 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. Each cell in column 3 contains analogous estimates without controlling for covariates. a: BA Degree (6 Years)[a]) is only estimated for Cohort 1. Robust standard errors in parentheses. * (p<0.10) **(p<0.05), ***(p<0.01).

Table IV: Heterogeneity in Treatment Effects by Presence of Suboptimal Baseline Preferences

	4-Year College (1)	Adjusted Grad Rate (2)	BA Degree (5-Years) (3)
Treatment*Suboptimal Index	0.0599***	1.547	0.0438*
	(0.0222)	(1.123)	(0.0246)
Treatment*Inv. Cov. Weighted Index	0.0352*	0.9540	0.0298*
	(0.0205)	(0.8440)	(0.0174)

Note: Table provides treatment effect estimates on various outcomes as well as how those treatment effects vary with the intensity of suboptimal baseline college preferences. Each column contains estimates from a separate regression of a dependent variable (in columns) on a treatment indicator variable and treatment indicator variable interacted with an index of the intensity of suboptimal baseline college preferences, controlling for site by cohort (i.e., risk set) indicators as well as the covariates indicated in Table 1. The intensity of suboptimal baseline college preferences is captured by an index that combines information from 12 different proxies for suboptimal baseline preferences. The proxies include listing a school with a below median 6-year graduation rate (53.8%) as well as the share of institutions listed with low graduation rates, listing a school with a below median 6-year graduation rate and a high net price (over $10,000) as well as the share of institutions listed with low graduation rates and high net prices, listing a school for which the residual from a regression of graduation rate on individual GPA and imputed SAT falls in the bottom 25 percent as well as the share listed meeting those conditions and the opposite of the average residual across baseline schools listed, listing a school in Barron's categories 4-6 (i.e., "Less Competitive", "Non-competitive", "Special"), listing a for-profit institution, listing a school with median earnings for individuals from low-income families ($0-$30,000) below the bottom quartile in MA or NY as well as the share listed meeting those conditions, and not listing a single "match" institution (i.e., an institution for which one's predicted SAT fell between the 25th and 75th percentile). The summary index was generated by first standardizing each measure to have mean zero and standard deviation one, adding the measures together, and then restandardizing. Robust standard errors in parentheses. * (p<0.10), ** (p<0.05), *** (p<0.01).

Table V: Mediation Analysis for 5-Year Bachelor's Degree Attainment

	(1)	(2)	(3)	(4)
Treatment	0.076***	0.017	0.021	0.018
	(0.022)	(0.019)	(0.021)	(0.022)
Adj. Grad. Rate		1.018***	0.934***	0.886***
		(0.031)	(0.113)	(0.013)
BL Target				0.062
				(0.088)
Adj. Grad. Rate Instrumented			X	X
BL Target Instrumented				X
Treatment Effect Explained by Quality		0.059***	0.055***	0.052***
		(0.011)	(0.012)	0.012)
Percent Explained		78.1%	72.2%	67.9%
Treatment Effect Explained by BL Target				0.007
				(0.009)
Percent Explained				8.6%

Note: Table provides summary information for a mediation analysis approach aimed at explaining estimated bachelor's degree treatment effects via shifts in initial enrollment quality (i.e., adjusted graduation rate) and target institution (those with available in-college Success advising) enrollment. See the text and the notes to Figure 4 for additional detail on the definition of the adjusted graduation rate. Each column in the top panel represents a separate regression. Column 1 reproduces the basic treatment effect estimate. Column 2 illustrates the effect of including the adjusted graduation rate as a mediator. Column 3 instruments for the adjusted graduation rate. Column 4 instruments for the adjusted graduation rate and initial enrollment at a target institution. As in our basic specification, we control for site by cohort (i.e., risk set) indicators and covariates in each regression. The bottom panel illustrates the extent to which each mediator explains the overall treatment effect. Bootstrapped standard errors in parentheses. * (p<0.10) **(p<0.05), ***(p<0.01).

Table VI: Survey Analysis of Advisors' Influence on Students

	Control Mean (1)	Treatment (2)
Panel A: Student Completion of College and Financial Aid Milestones:		
Filled Out FAFSA	0.97	0.017
		(0.014)
Apply for Private Scholarship	0.525	-0.006
		(0.041)
Proportion Applying	0.988	0.009
		(0.008)
Number of Applications	9.75	2.92***
		(0.384)
Accepted (Proportion)	0.63	0.028
		(0.022)
Offered Aid	0.745	0.004
		(0.033)
Offered Aid (Proportion)	0.642	0.011
		(0.031)
Met to Review Award Letter	0.67	0.176***
		(0.039)
Panel B: Student Sentiment and Topics Discussed:		
Sentiment Analyses		
Positive	0.240	0.294***
		(0.067)
Negative	0.400	0.151**
		(0.067)
Topical Analyses		
Gratitude	0.200	0.290***
		(0.066)
Difficulty	0.520	0.129*
		(0.069)
Adult Assistance	0.170	0.150**
		(0.061)
Lack Support	0.160	-0.142***
		(0.045)

Note: Table provides estimated treatment effects on measures generated from a survey of the first experimental cohort. Panel A contains estimated treatment effects on student completion of college and financial aid milestones. Panel B contains estimated treatment effects on the sentiment and topical content of student free-form responses when asked to provide additional information about their "college decisions or the application process as a whole." See the text and Appendix E for additional discussion and a detailed description of how these measures were extracted from the textual data using natural language processing (NLP) and human coders. In Panel B, we present estimated treatment effects on the union of human coder measures (i.e., if either coder indicated a response mentioned the "difficulty" of the process, we coded that student as indicating difficulty). We demonstrate the robustness of the estimates to alternative measures in Appendix E. Column 1 contains control group means. Each cell in column 2 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).