An Engine of Economic Opportunity: Intensive Advising, College Success, and Social Mobility*

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Abstract

Inequalities in American higher education contribute to low social mobility. We combine a large multi-site randomized control trial with administrative and survey data to provide evidence on the role of college counseling in addressing these disparities. We find that a coordinated model of intensive advising during high school and college leads to large effects on college enrollment and persistence and shifts students towards higher-quality institutions (higher graduation rates, lower loan default rates, higher social mobility rates). Program effects are remarkably consistent across time, counselors, and student characteristics, suggesting the model is highly scalable; broad adoption could cut the income-gap in college enrollment in half.

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1 Introduction

Social mobility in the United States has declined steadily over time. Only 7.5 percent of people born into the bottom income quintile will advance to the top income quintile over the course of their lives, and where children fall in the income distribution by age 30 is strongly related to their parent's place in the income distribution (Chetty et al., 2017). These linkages are particularly acute for minorities, potentially contributing to the emergence and persistence of achievement gaps by race/ethnicity.

A college education remains an effective channel through which children born into low-income families can achieve greater economic opportunity. Among those born to parents in the bottom quintile, those who attend college are two and a half times as likely to make it to the top income quintile. Those who attend an elite college have a higher chance of making it to the top than those who were born in the top income quintile. (Chetty et al., 2017).

The rise in the importance of the role of college in promoting social mobility has paralleled the rise in the returns to postsecondary education, 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; Zimmerman, 2014). At the same time, socioeconomic gaps in college completion have widened; 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). Differences in preparation explain some of the attainment gap, but disparities in college success by family income persist even upon control for academic achievement (Bailey and Dynarski, 2011; Belley and Lochner, 2007). There are also pronounced socioeconomic gaps in where students go to college. At the roughly one thousand selective colleges in the US, there are more students from the top 10% than the bottom 40% of the family income distribution. (Chetty et al., 2017).[1]

While financial differences likely play a role in persistent attainment gaps, increasing evidence suggests that a lack of family financial resources may not be the primary driver of these disparities (Bulman et al. 2017). Despite decades of federal and state financial aid policies, and hundreds of

[1] This includes colleges in Barron's Tiers 1-5, which account for roughly half of college enrollment.

billions of dollars distributed in need-based financial assistance, the attainment gap between high- and low-income students continues to grow.

More recently, attention has turned to the importance of light touch strategies (information and assistance) in influencing college choices (for example, Bettinger et al. 2012). While evidence suggests that these nudges can play a role, the impacts are generally modest, and it is not yet clear whether the results translate into meaningful effects on degree attainment. One theme that has emerged from this work is the importance of professional assistance in supporting students to navigate complex and consequential decisions, like deciding where to apply to college or completing financial aid applications. In this paper, we investigate the impact that professional and intensive college counseling can have on postsecondary enrollment and success for low-income populations.[2]

Federal and state governments and many communities have invested in professional, intensive college advising programs as a supplement to the limited college counseling students receive within their high schools, and 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 (twice the number of high-school charter students) — 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. We also know of no evaluation of an intensive advising program that begins working with students at the start of the college application process and that continues working with students for up six years following high school graduation. Our paper contributes new, precisely-identified evidence of an intensive college advising program providing this kind of "to and through" support on low-income students'

[2]The distinction between professional and intensive college counseling and counseling that students receive from their high school counselor is important. College counseling only accounts for approximately 20 percent of the typical high school counselor's workload. Most high school counselors have limited training or experiencing advising students on financial aid or college choice decisions.

college access and persistence.[3] 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, drawing students from several hundred high schools.[4]

The BL model is divided into two distinct stages: Access counseling and Success counseling. Access counselors provide individualized advising to students from the summer before senior year of high school through the summer after high school. BL 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. Counselors work with students on identifying well-matched colleges to apply to and on completing and submitting college applications. Counselors encourage students to attend a set of target colleges and universities that BL has identified as providing students with an optimal combination of quality and affordability. Many of these institutions appear to promote social mobility for their students, with relatively large shares of students born into low-income families ending up substantially higher in the income distribution. Success counseling is a unique component of the BL model. 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 more likely to enroll in college in the fall after high school graduation. 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. Our estimates suggest that counseling would be even more effective for more disadvantaged students and in areas with less college supports. Among

[3] Bottom Line serves students from families that make less than 200 percent of the federal poverty line.

[4] Bottom Line is also in the process of exploring scaling to additional states. BL's site in Chicago opened in 2014 and is not included in our analysis.

those in the bottom quartile of predicted four-year enrollment, the estimated treatment effect is 15.1 percentage points, a 31 percent increase off a mean of 49 percent.

While not statistically different from the estimated effects on enrollment in the fall after high school graduation, the estimated 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. We attempt to decompose impacts of Access counseling and Success counseling, and find suggestive evidence that the persistence of impacts is largely due to BL's continued counseling presence during college. Specifically, treated students at *BL target schools* are 6.8 percentage points more likely to persist into the second year than those in the control group at the same colleges. In contrast, there is a smaller and non-significant difference in the persistence of treated students at non-target schools. This suggestive evidence of the positive impact of advising for students while they are in college aligns with other experimental evaluations demonstrating sizeable improvements in academic performance and degree attainment for students assigned to college success coaching (Bettinger and Baker, 2014; Oreopoulos and Petroniviejic, 2018).

The BL model also has a substantial effect on where students enroll in college, leading students to attend colleges and universities that have higher graduation rates, that have lower loan default rates, and that appear to promote social mobility. Drawing on Chetty et al's (2017) estimates of the relationship between college going and mobility, our results suggest that access to counseling results in students attending colleges or universities where the average chance that students from the bottom quintile move into the top quintile of the income distribution is 21 percent higher than at the colleges and universities attended by control group students.[5] BL impacts appear to be largest for those we predict to be least likely to succeed, for those at high-poverty schools, and for those in communities with the fewest alternative college advising resources and lowest high school counselor-to-student ratios, which further suggests the model, if expanded broadly, could meaningfully improve both postsecondary educational opportunity and social mobility for

[5]We note here and in subsequent sections of the manuscript where we are discussing the impact of Bottom Line on the quality of institutions that students attend that these mobility estimates indicate an effect on the characteristics of the colleges attended by students and not an effect on the mobility of the treated students themselves. While students are attending schools where the average earnings and chances of mobility are higher, we cannot say at this stage of the evaluation whether Bottom Line improves students' own incomes or economic mobility.

low-income students.[6]

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.[7] 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.[8]

A significant question about our findings is whether the BL model is likely to be scalable to different contexts and populations. While students with low predicted outcomes and 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. Despite consistent impacts across cohorts and student sub-groups, BL could nonetheless 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.[9] 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.[10] This lack of heterogeneity across different types of counselors suggests that BL has

[6]Further supporting this scalability argument, the colleges targeted by BL account for a substantial (40%) and responsive share of nearby four-year enrollment, suggesting that BL is not just crowding out other students.

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

[8]Recent research on "summer melt" suggests that, even after students have applied and been accepted to college and applied for financial aid, 10 â 20 percent of students nationally fail to enroll anywhere in the year after high school as a result of unforeseen and complicated financial aid procedural tasks they have to complete during the summer after high school graduation (Castleman and Page, 2014). Several interventions demonstrate that providing students additional information and assistance during the summer after high school can lead to higher rates of enrollment, with impacts particularly pronounced among low-income and first-generation students (Castleman and Page, 2014; Castleman and Page 2015). These interventions focused substantially on addressing financial barriers to enrollment, which is consistent with the results from the BL survey indicating treated students were much more likely to engage in important conversations about college finances than were control students.

[9]Student baseline characteristics are balanced across counselors, consistent with random assignment.

[10]An F-test on the counselor fixed effects indicates that we cannot reject the null of equivalent counselor effects on college enrollment (p-value of 0.489) and four-year college enrollment (p-value of 0.902).

a well-developed set of counselor recruitment, selection, training, and development processes for ensuring counselor success, and supports the potential for broad scalability of the model, since results do not appear to be driven by a small set of particularly high-performing counselors.[11]

Our study is one of few studies to rigorously evaluate whether intensive college counseling influences the postsecondary educational choices of low-income individuals, and the extent to which these choices may affect college success and the quality of institutions that students attend. Among randomized control trials of counseling interventions, Carrell and Sacerdote (2017) find evidence that a combination of peer mentoring and fee waivers led to substantial increases in the share of female students who completed at least two years of college, while Avery (2013)'s pilot RCT of a program (N=238) providing standardized test tutoring in addition to assistance with college choice and applications found positive effects on four-year enrollment.[12] Yet neither study finds precisely estimated impacts for the overall sample, and the Carrell and Sacerdote experimental sample is relatively well off financially (only roughly a quarter are eligible for free or reduced price lunch) and lacked racial/ethnic heterogeneity (80% of the sample was White). Bos et al. (2012) study a somewhat poorer and more Hispanic population in Los Angeles, finding no overall effects on enrollment or four-year enrollment of a similar near-peer mentoring program. Other evaluations of large-scale counseling programs (such as the federally-funded Upward Bound program) found no impact on enrollment (Seftor, Mamun, and Shirn, 2009).[13] By comparison, our study provides precisely estimated evidence that, for poor children, intensive counseling is effective in both increasing enrollment and shifting students towards higher-quality colleges.

Our results also build on these prior experimental studies of college advising programs in several additional 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 college

[11] 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.

[12] Avery also has two interesting small-scale studies (Avery 2010; Avery 2014) that focus on *very high achieving students* and the extent to which mentoring (or tele-mentoring) can influence college match, finding suggestive effects on college match.

[13] In a somewhat different context, Ontario, Oreopoulos and Ford (2016) evaluate a schoolwide intervention in which students participated in a series of school-based workshops in which they received guidance on choosing postsecondary programs to pursue, completed applications, and applied for financial aid. Students assigned to these workshops were 2.9 percentage points more likely to go to college, but the effect was driven entirely by increasing enrollment at community college, and the study does not provide longitudinal data on whether treated students persisted in college at higher rates.

(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 persist and grow over time.

In addition to prior experimental evaluations of intensive college counseling interventions, our paper makes meaningful contributions to the quasi-experimental literature on college advising programs. Of particular relevance is a regression discontinuity design evaluation of the BL program in the Boston area (Castleman and Goodman, 2016). While this study finds corroborating evidence that BL positively impacts college persistence, the paper's results are imprecisely estimated, rely on a manipulable running variable, and are local to the 2.5 GPA threshold determining eligibility for the program.[14] Moreover, Castleman and Goodman (2016) are not able, by virtue of the research design or data, to investigate several of the important questions that we examine in the current paper, such as the decomposed effects of Access vs. Success counseling, the heterogeneity of impacts by BL counselor, or the mechanisms through which BL counseling affects students' decisions and outcomes.

Our study moreover identifies 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).[15] 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.

Our survey results, detailed counselor-student interaction data, and quasi-random counselor assignment also provide valuable evidence about *how* programs like BL affect student outcomes. For instance, our results suggest 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, our back-of-the-envelope cost-benefit estimates (which we elaborate upon in the discussion of the paper), suggest that the earnings gains as a result of the program could exceed BL's costs (approximately $4,000 per offered student) in a single year. The high rate of return and

[14] For example, Castleman and Goodman's estimates on four-year enrollment include effects as small as *negative* 20 percentage points and as large as 40 percentage points.

[15] Carrell and Sacerdote also provide students with a $100 bonus for participating in mentoring in most years. In the year that they removed this bonus, mentoring take-up fell 33 percentage points, further suggesting the importance of small financial incentives.

the consistency of effects across time, counselors, and student characteristics, suggest the model is highly scalable. 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.[16]

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. Based on a market analysis BL contracted a consulting firm to conduct in its Massachusetts markets, the program serves a sizeable share of the students that meet the program eligibility requirements in in its focal cities – 60-70 percent in the Boston area (i.e., the Boston and Worcester sites). The high rate of take up suggests that were BL to scale, it would likely reach most eligible students in small/medium cities. While BL was not operating in New York at the time of the market analysis, the firm's estimates suggest that BL's current reach in New York (approximately 300 students) only serves a small share of the roughly 12,000 students in the city who meet the program eligibility requirements.

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

[16] Based on a comparison of the college enrollment rates of high-school graduates with GPAs over 2.5 from families above and below 185 percent of the poverty line (authors' calculations using the High School Longitudinal Study of 2009 (HSLS: 09)).

caseload of 50-60 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 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. Outside of direct time with students, counselors are working on additional advising-related activities, like developing customized college lists for students, reviewing students' college essays, and analyzing students' award letters. 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.[17] 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 adjust meeting frequency based on student need, meeting more regularly with students who are experiencing some form of challenge in college. Success counselors typically serve students across 2-3 different campuses, and work with 30-40 students per campus. Counselors provide a combination of academic support (e.g. course selection and making use of advising and tutoring services), social support (e.g.

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

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.[18]

While the core of the model is the counselor-student relationship, Bottom Line also facilitates supplemental student group experiences as students enter the Success program. Each summer after high school, Bottom Line hosts a "Success Send-off" event at the middle or end of August in each region. Once students have matriculated, Bottom Line hosts periodic (once a semester) "socials" for Bottom Line students at the campus to connect with each other. In some instances Bottom Line facilitates mentoring relationships between upperclass students and new students, but this is not a formal component of the program.

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 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 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.

[18] In addition to student-facing activities, BL counselors participate in curriculum training sessions, college visits and knowledge building, and management of partner relationships with schools and other community-based organizations. In advance of when applications are due staff visit schools to do recruitment sessions and help review new applications as they come in.

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 2 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 2 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.[19]

One item of note is that enrollment rates are relatively high for BL applicants even in the absence of treatment (82.7%). While this is only slightly higher than the national rate of enrollment for similarly situated but slightly poorer high-school graduates (72%), it begs the question: would counseling be more effective for more disadvantaged students and in areas with less college supports?[20] To explore this, we present treatment effect estimates for those in the bottom quartile of each predicted outcome.[21] The estimates are substantially (33 to 47%) larger within this subsample (Appendix Table A5). Among those in the bottom quartile of predicted four-year enrollment, the estimated treatment effect is 15.1 percentage points, a 31 percent increase off a mean of 49 percent, suggesting that the program may be even more effective for those facing greater disadvantage.[22]

Similarly, BL impacts appear to be larger for students from high-poverty high schools and in communities with the fewest college supports. For students from schools above the median level of free and reduced price lunch, those assigned to treatment are 13 percentage points more likely to enroll in a four-year college.[23] In Worcester, the site with the fewest alternative college advising resources and lowest high school counselor-to-student ratio, those assigned to treatment are 18 percentage points more likely to enroll in a four-year college, a 33 percent increase off a base of 53 percent.[24]

Drawing on Chetty et al's (2017) estimates of the relationship between college going and mobility, Table 3 contains estimates of the treatment effect on predicted mobility and earnings.[25] Specifically, we assign each individual the mobility rate (from bottom to top quintile) and median

[19]The estimates from specifications without covariates are similar (Appendix Table A3). Given the differential probability of treatment assignment across sites, we also present average marginal effects from specifications that interact risk-set indicators with treatment status. These specifications account for potential heterogeneity in treatment effects across sites; the estimated average treatment effects are similar (Appendix Table A4).

[20]72% of high-school seniors with at least a 2.5 GPA and from families below 185% of the poverty line enroll in college in the fall after high-school graduation (authors' calculations from High School and Beyond.

[21]Specifically, we predict each outcome using baseline observables and outcomes in the control group (following a leave one out procedure to avoid bias for control group observations). We then estimate our basic specification for individuals with a predicted outcome in the bottom quartile.

[22]Although, we note that these estimates are not statistically different from our full sample estimates.

[23]The point estimate is 0.130*** (se, 0.025) for four-year enrollment and 0.094*** (se, 0.022) for overall enrollment.

[24]The point estimate is 0.177*** (se, 0.059) for four-year enrollment and 0.084* (se, 0.046) on overall enrollment. Alternative college advising resources are measured using baseline measures from the Bottom Line application of whether students had prior interactions with other college access organizations and confirmed in discussions with Bottom Line staff. Counselor ratios are constructed from the Civil Rights Data Collection/Data Set for 2013-14, obtained at https://www2.ed.gov/about/offices/list/ocr/docs/crdc-2013-14.html

[25]We note that the Chetty estimates are not causal and are careful to use language that does not imply a causal effect on the average mobility or earnings of the choices made by sample members.

earnings associated with where they are observed enrolled. For those not enrolled, we assign the mobility rate and median earnings associated with non-enrollees. Our results suggest that access to counseling results in students attending colleges or universities where their average chance of moving into the top quintile of the income distribution is 21 percent higher and the median annual earnings are 14 percent higher (over $4,000).[26] Focusing on students with predicted outcomes in the bottom quartile, we see even larger effects: a 28 percent increase in the average mobility and an 18 percent increase in the median annual earnings of the institution they attend. These results support the role of counseling in helping those at greatest disadvantage and indicating that the program may be even more effective if scaled to the broader population.

Further supporting this scalability argument, the colleges targeted by BL account for a substantial (40%) and responsive share of nearby four-year enrollment suggesting that BL is not just crowding out other students. Between 2003 and 2014, enrollment at BL target colleges rose nearly 30 percent (7,690 students), while enrollment at Ivy league institutions in the same areas rose roughly 3.6 percent (142 students).[27] BL target institutions also appear to increase capacity in response to demand; regressing log enrollment on log applications in first differences indicates that enrollment rises by 5.4 percent for every 10 percent increase in applications. In contrast, enrollment levels at elite and Ivy league institutions are unresponsive to the number of applications.[28]

Estimated treatment effects are somewhat larger for female students and individuals with lower high-school GPAs, but these sub-group differences are not statistically distinguishable. Our estimates of the effects of counseling are generally quite similar across subgroups (Table 4). There is no meaningful (or statistical) difference in the estimated effect of the program when comparing black and hispanic versus white and Asian 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

[26] These estimates combine an enrollment effect with a choice effect. Appendix Table A6 contains estimates conditional on enrollment. These estimates also suggest substantial shifts in college choice, but lose their causal interpretation as they condition on an endogenous variable (enrollment).

[27] Based on authors' calculations using IPEDS data restricted to commuting zones containing the BL target colleges. Were BL primarily targeting students towards highly selective institutions with limited changes to total enrollment over time (e.g., the Ivies), the concern about crowd out would be more pronounced.

[28] The point estimate for BL target institutions is 0.54 (se, 0.043), while that for Ivy and elite institutions is -0.02 (se, 0.021).

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 and may be even more effective if scaled to populations and communities with fewer college-going supports. 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. 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. 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.[29]

5 Mechanism

The size and persistence of effects leads to a natural question: why is this model of college counseling so effective? In this section, we attempt to more rigorously measure what counselors do and

[29] As before, the effects are quite similar across subgroups, with large increases in 2nd year enrollment and measures of attainment for all types of individuals. The results for persistence in four-year college are contained in Appendix Table A7.

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 6 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 6 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 56 percent of students responded to the survey, with roughly equal response rates among treatment and control group students.[30]

[30]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 A8 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,

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 (Table 7). 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 ($\approx$ 60 percent), counselors ($\approx$ 50 percent), and teachers ($\approx$ 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.

the characteristics of treated respondents are broadly similar to control respondents.

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.[31]

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.[32]

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

[31]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.

[32]We note that it is, of course, possible that the quality of counselors falls with expansion, but argue that the consistency of effects across current counselors suggests the importance of the BL model to ensuring consistent delivery of services.

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).[33] While interesting in its own right, the lack of heterogeneity across different types of counselors further suggests the scalability of the program.[34] 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. 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).[35] 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.

[33] 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.

[34] We have also investigated the presence of racial or gender interaction effects (for example, does a black student benefit more from a black counselor). While power limits our ability to draw strong conclusions, we find no evidence of important interactions of this type.

[35] 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.

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 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.[36]

When we control for baseline student characteristics, the point estimate grows to 4.7 percentage points, consistent with the argument that BL drew in more marginal students. 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

[36] Indeed, the estimates in Appendix Table A5 suggest this was likely the case, with substantially larger effects among those predicted least likely to enroll or enroll in a four-year college. For example, among those in the bottom quartile of predicted four-year enrollment, the estimated treatment effect is 15.1 percentage points, a 31 percent increase off a mean of 49 percent. A comparison of the high-school GPA distributions of enrolled treatment and control students similarly suggests that the intervention may have brought in slightly more marginal students, although the distributions are not significantly different (Appendix Figure A1).

lower bound for the effectiveness of the continued counseling presence at BL target colleges.

6 Discussion

Through a multi-cohort, multi-site RCT, we provide robust evidence that intensive counseling positively influences the educational choices of low-income individuals. Our paper is moreover the first of which we are aware that rigorously investigates the impact of intensive college advising programs on college choice through the lens of social mobility, leveraging recently-available data on institution-level social mobility rates from Chetty et al. (2017). We demonstrate that the BL model leads students to attend institutions of higher quality based on traditional metrics (e.g. graduation rate and cohort loan default rate) and newer measures of social mobility, the fraction of students moved from the bottom to the top income quintile. More specifically, students offered counseling attend colleges or universities where their chances of moving into the top quintile of the income distribution are 21 percent greater than those in the control group. Given declining social mobility over time, the counseling appears to be an effective policy strategy to promote greater economic opportunity for economically-disadvantaged but academically college-ready students.

In addition to our focus on poor students and social mobility, 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. The latter result appears to be driven by the ongoing college counseling BL provides to students who attend one of their target institutions. 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 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 large 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. Of course, it is possible that the quality of BL counselors could fall with program expansion in an area, but high rates of take up in the Boston area (BL reaches 60-70% of eligible students) suggest that counselor quality can be maintained.

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.[37] 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.

On the other hand, it is possible that the quality of students (or their responsiveness to treatment) might decrease with program expansion. While our intuition and results suggest that the worse prepared and less motivated students are most helped by the program, it is possible that those most resistant to signing up, and thus not part of our experimental sample, might actually have less to gain from participating in the program. Regardless, it is clear that BL is quite effective for the large share of eligible students who apply to participate in the program.

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 estimates in Table 3 suggest that the earnings gains as a result of the program could exceed BL's costs (approximately $4,000 per offered student) in a single year.[38] 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 of enrollment effects makes it difficult to estimate cost-effectiveness, particularly for poor individuals. 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

[37] In Worcester, the site least saturated with alternative college access programs (as measured by entry questionnaire participation and confirmed in discussions with Bottom Line staff), we observe the largest effects of the program.

[38] Using a more standard approach assuming an average return to a degree, the BL model passes a cost-benefit test under very conservative assumptions on the eventual effects on degree completion. 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.

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 and beyond.

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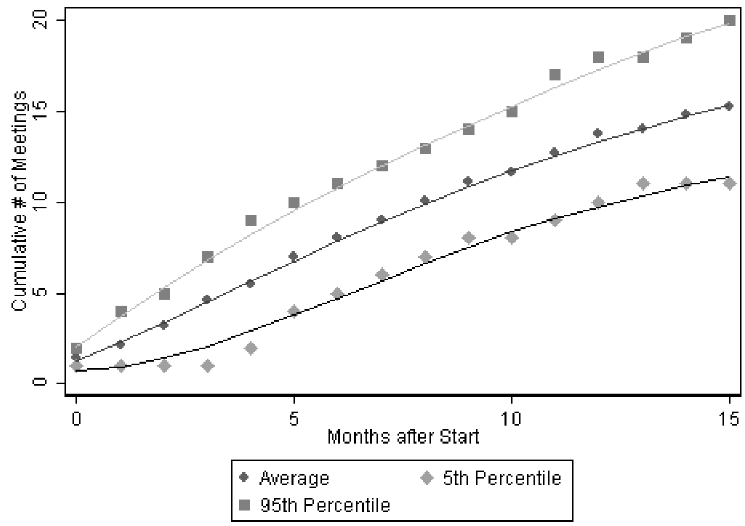
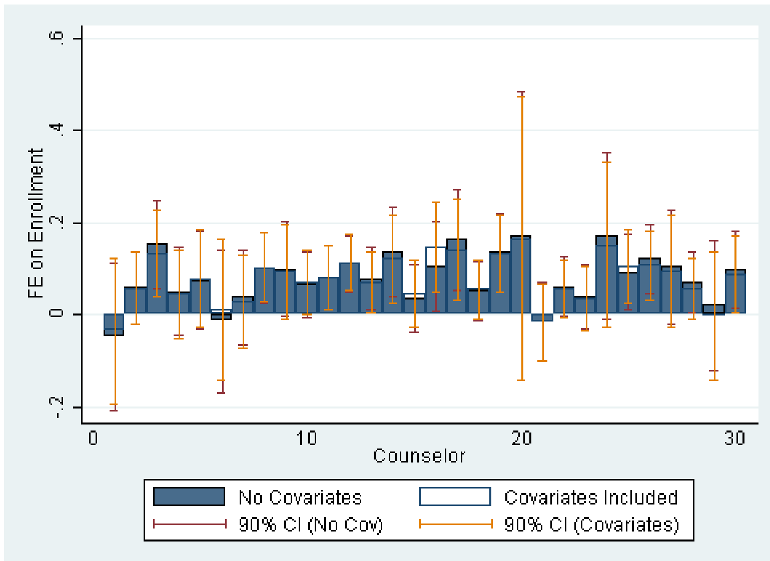
Figure 1: Counselor Interaction Patterns over Time

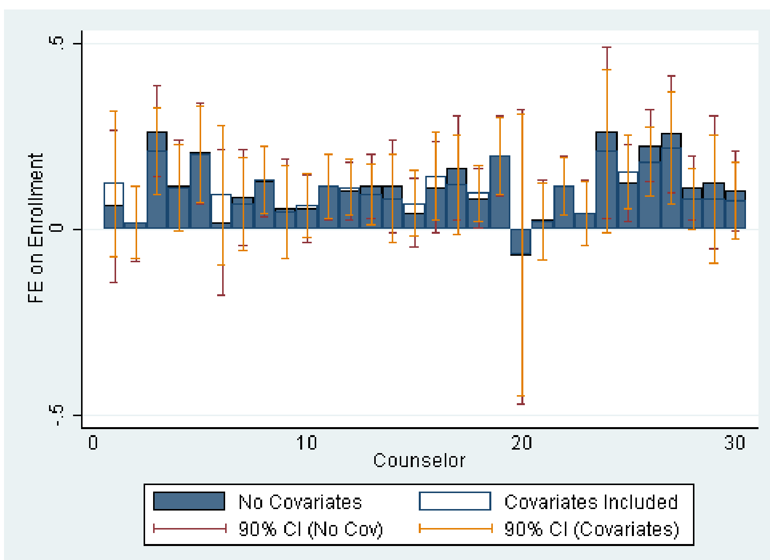


Note: Statistics derived from BL data. Month 0 is May of each high school class' junior year.

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	0.435	0.053**	0.353	0.060**	0.597	0.039
		(.024)		(.029)		(.034)
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	0.489	-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: 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 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 3: Effects on Predicted Mobility and Earnings

	Full Sample		Q1 Predicted Outcome*	
	Control Mean	Treatment	Control Mean	Treatment
	(1)	(2)	(3)	(4)
Mobility from Bottom to Top 20 (in logs)	3.004	0.211***	2.631	0.278***
		(0.034)		(0.074)
Median Earnings (in logs)	10.45	0.138***	10.23	0.181***
		(0.024)		(0.053)
Observations		2422		605

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. Outcome variables assume mobility rates and median earnings of non-enrollees from Chetty et al. (2017). *Columns (3) and (4) contain estimates from estimating the basic specification after restricting the sample to the bottom quartile based on the predicted outcome of the dependent variable in each row (using a leave one out procedure to avoid bias in the predicted outcome). Robust standard errors in parentheses. * (p<0.10) **(p<0.05), ***(p<0.01).

Table 4: Effects on 4-Year College Enrollment: Heterogeneity

Variables	(1)	(2)	(3)	(4)	(5)
Treatment	0.116***	0.104***	0.099***	0.085***	0.102***
	(0.022)	(0.029)	(0.027)	(0.025)	(0.025)
Treatment * Male	-0.050				
	(0.038)				
Treatment * Black		-0.023			
		(0.042)			
Treatment * Hispanic		0.014			
		(0.042)			
Treatment * No Other Program			0.004		
			(0.035)		
Treatment * Low GPA				0.033	
				(0.035)	
Treatment * Low AGI					-0.001
					(0.035)
Observations	2,420	2,422	2,422	2,422	2,419
Omitted Group Mean	0.774	0.820	0.774	0.874	0.799
Interaction Group Mean	0.762	0.759/0.721	0.766	0.660	0.660

Note: Each column represents a separate regression of four-year college enrollment on a treatment indicator variable and its interaction with membership of an indivdiual in a subgroup of interest, 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	Treatment
	(1)	(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: 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 7: Student Completion of College and Financial Aid Milestones (Cohort 1)

	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		813

Note: Odd columns contain control group means. 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).

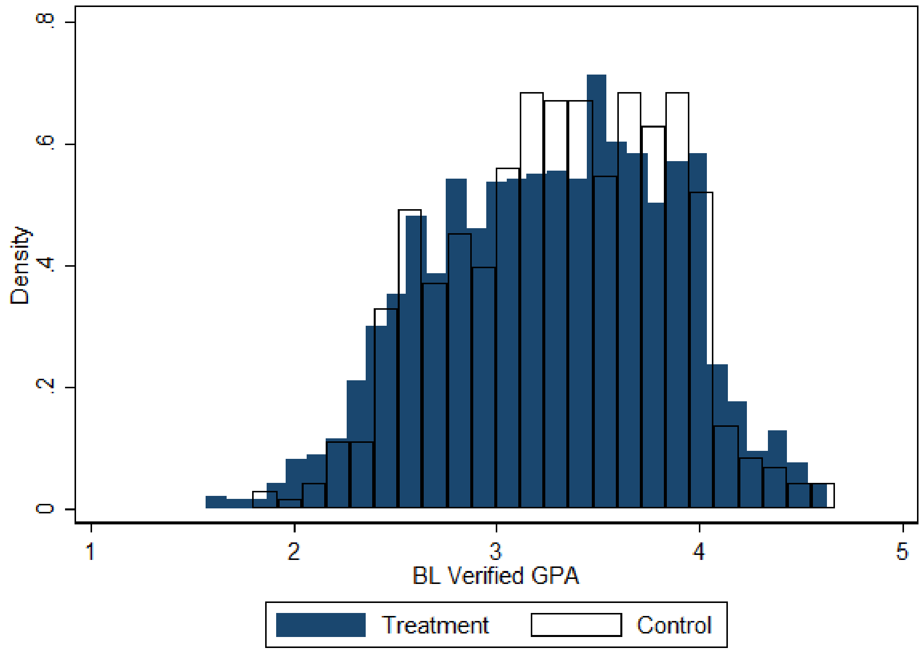
Table 10: Effects on Persistence in College (conditional on first-year enrollment)

	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

Figure A1: GPA Distributions of Enrolled Students



Note: Statistics derived from BL data for those observed enrolled in fall after senior year.

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: Treatment and Control Assignments

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

Table A3: Effects on Enrollment in College (no covariates)

	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	0.066***	0.841	0.056***	0.807	0.080***
		(0.016)		(0.020)		(0.026)
Enrolled 4-Year College	0.703	0.103***	0.712	0.105***	0.691	0.102***
		(0.020)		(0.026)		(0.031)
Enrolled 2-Year College	0.127	-0.039***	0.129	-0.049**	0.123	-0.025
		(0.015)		(0.019)		(0.023)
Observations		2422		1429		993

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. Robust standard errors in parentheses. * (p<0.10) **(p<0.05), ***(p<0.01).

Table A4: Effects on Enrollment in College (interact lottery indicators)

	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	0.061***	0.841	0.050***	0.807	0.077***
		(0.017)		(0.021)		(0.028)
Enrolled 4-Year College	0.703	0.099***	0.712	0.100***	0.691	0.097***
		(0.021)		(0.026)		(0.033)
Enrolled 2-Year College	0.127	-0.039**	0.129	-0.050***	0.123	-0.022
		(0.015)		(0.020)		(0.023)
Observations		2422		1429		993

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

Table A5: Effects on Most Disadvantaged Students

	Q1 Predicted Outcome	
	Control Mean	Treatment
	(1)	(2)
Enrolled Any College	0.73	0.093**
		(0.037)
Enrolled 4-Year College	0.49	0.151***
		(0.045)
Observations		605

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. Q1 estimates restrict sample to bottom quartile based on the predicted outcome of the dependent variable in each row (using a leave one out procedure to avoid bias in the predicted outcome). Robust standard errors in parentheses. * (p<0.10) **(p<0.05), ***(p<0.01).

Table A6: Effects on Predicted Mobility and Earnings (conditional on enrollment)

	Control Mean (1)	Treatment (2)
Mobility from Bottom to Top 20 (in logs)	3.323	0.11.1*** (0.021)
Median Earnings (in logs)	10.69	0.059*** (0.011)
Observations		2063

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. Regressions restricted to individuals observed enrolled in the fall after senior year. Robust standard errors in parentheses. * (p<0.10) **(p<0.05), ***(p<0.01).

Table A7: Effects on Persistence in Four-Year College: Heterogeneity (Cohort 1)

Variables	(1)	(2)	(3)	(4)	(5)
Treatment	0.115***	0.135***	0.130***	0.107***	0.134***
	(0.023)	(0.030)	(0.029)	(0.026)	(0.026)
Treatment * Male	-0.001				
	(0.040)				
Treatment * Black		-0.036			
		(0.044)			
Treatment * Hispanic		-0.030			
		(0.044)			
Treatment * No Other Program			-0.027		
			(0.037)		
Treatment * Low GPA				0.015	
				(0.037)	
Treatment * Low AGI					-0.039
					(0.037)
Observations	2,420	2,422	2,422	2,422	2,419
Omitted Mean	0.717	0.789	0.722	0.846	0.735
Interaction Mean	0.698	0.691/0.636	0.701	0.568	0.568

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 A8: Survey Response Balance

	Full Sample	Respondents	
	Control Mean	Control Mean	Treatment
	(1)	(2)	(3)
Female	0.697	0.755	-0.051
			(0.035)
Black	0.302	0.335	-0.029
			(0.036)
Hispanic	0.325	0.335	-0.018
			(0.037)
Asian	0.246	0.265	0.033
			(0.036)
Other Race	0.094	0.086	0.009
			(0.023)
Citizen	0.787	0.767	-0.070**
			(0.034)
Verified GPA	3.264	3.320	0.018
			(0.043)
Parent AGI	22520	22295	-720
			(1456)
Household Size	4.26	4.32	-0.014
			(0.13)
Mom Employed	0.641	0.532	-0.017
			(0.040)
Mom Employed (missing)	0.144	0.171	-0.040
			(0.028)
Dad Employed	0.435	0.352	0.069*
			(0.039)
Dad Employed (missing)	0.446	0.494	-0.040
			(0.040)
First Generation	0.811	0.820	-0.048
			(0.032)
Sibling College	0.389	0.367	0.010
			(0.039)
Sibling College (missing)	0.059	0.053	-0.002
			(0.017)
Sibling Bottom Line	0.075	0.053	0.017
			(0.019)
Sibling Bottom Line (missing)	0.074	0.065	0.009
			(0.021)
Other Program	0.444	0.412	-0.047
			(0.038)
Observations	2422	813	

Note: Column (1) contains control group means for the full sample. Column (2) contains control group means for survey respondents. Each cell in column (3) 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. Response rates did not differ significantly between control and treatment groups. Response rate for control group was 0.558, with a 0.016 (se 0.029) coefficient on a treatment indicator variable, controlling for site by cohort indicators. Robust standard errors in parentheses. * (p<0.10) **(p<0.05), ***(p<0.01).

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.[39] 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 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 be-

[39]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.

tween 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.[40]

[40]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	Index Enrolled 4-Year	Index Semesters	Index Cont. Enrolled
	(1)	(2)	(3)	(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).