Beyond Teachers:
Estimating Individual Guidance Counselor's Effects on Educational Attainment

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Abstract

Guidance counselors are a common school resource for students navigating complicated and consequential education choices. I provide the first causal estimates of individual counselors' effects on high schoolers, using quasi-random counselor assignment policies in Massachusetts. I find that counselors vary substantially in their effectiveness at increasing students' high school graduation rates and college attendance, selectivity and persistence. Counselor effects on educational attainment are similar in magnitude to teachers' effects, but they flow through improved information and direct assistance, rather than through improved cognitive or non-cognitive skills. Counselor effectiveness is most important for low-achieving and low-income students, perhaps because these students are most likely to lack other sources of information and assistance. Good counselors tend to improve all measures of educational attainment but some specialize in improving high school behavior while others specialize in increasing selective college attendance. Improving access to effective counseling may be a promising way to increase educational attainment and close socioeconomic gaps in education.

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1 Introduction

High school students face hundreds of choices that have significant long-term effects on educational attainment and labor market outcomes. Students must decide which courses to take, how much effort to invest in school, whether and where to pursue postsecondary education, and what careers to explore. Many people, especially adolescents, lack the information and capacity needed to optimally navigate complex choices like these (Bhargava, Loewenstein & Snydor, 2017; Gennaioli & Shleifer, 2010; Hastings, Neilson & Zimmerman, 2015; Heller et al, 2017; Hoxby & Avery, 2013; Jensen, 2010).

In part because of this complexity, many school systems employ guidance counselors.[1] High school guidance counselors may help students understand the returns to education and careers, provide assistance which lowers the costs of applying to college, and recommend specific secondary and postsecondary pathways. In the U.S., for example, counselors are the second largest group of educators and public schools spend billions of dollars a year on them. Counselors typically serve many students, with average caseloads close to 250 students in high schools, so small changes in one counselor's effectiveness can impact many students.[2] Counselors' potential to affect college success and reduce educational inequity has drawn national attention and inspired policy changes, such as Michelle Obama's *Reach Higher* initiative and the expansion of counselor hiring in Colorado and New York City. The private college counseling industry is also rapidly growing, indicating both that people believe counselors play an important role in college outcomes and that publicly funded counseling is not sufficiently meeting demand for such services.[3]

This paper provides the first quantitative evidence on the causal effects of individual high school guidance counselors. School counselors are largely neglected by the literature, especially

[1] I refer to general high school counselors, now called school counselors, as guidance counselors for clarity. While the profession has moved away from the term guidance counselor, I use it in this context since it is still used by many schools in my sample and it helps clarify the type of counselor on which my research is focused. More details on the preferred title for counselors is available here `https://www.schoolcounselor.org/asca/media/asca/Careers-Roles/GuidanceCounselorvsSchoolCounselor.pdf`.

[2] The Common Core of Data indicates that, in 2017, there was one secondary school counselor per 237 students. This may, however, understate caseloads since it includes secondary school counselors who are not guidance counselors. National survey data indicate that the average high school caseload is 286 students (Clinedinst & Patel, 2018).

[3] There are more than 8,000 private college counselors, whose services cost approximately $5,000 (Sklarow, 2018). There are also a growing number of non-profits providing college counseling to low-income and minority students.

compared to the huge volume written on teachers. I demonstrate that counselors are an important element of the education production function and that their effects are largely driven by providing students information and direct assistance, such as recommendation letters and SAT fee waivers. Counselor effects on educational attainment appear similar in magnitude to teacher effects.

I leverage the quasi-random assignment of students to counselors in many Massachusetts high schools to causally identify the impacts of individual counselors on student outcomes. In about a third of Massachusetts high schools, students are assigned to counselors based on the first letter (or two) of their last name. These assignments vary over time and across schools based on the distribution of student names in a school and the student-to-counselor ratio. I estimate the impact of a student's first assigned counselor on her outcomes by using these rules as an instrument and controlling for the first letter of the student's last name, year, school, demographics, and eighth grade test score. This paper consists of five main findings.

First, I show that counselors significantly vary in their influence on high school graduation, college enrollment, selectivity and persistence. The standard deviations of counselor effects on high school graduation and four-year college attendance are about two percentage points. Their effects on college persistence are slightly smaller but still statistically significant. Leave-year-out estimates of effectiveness are valid out-of-sample predictors and they indicate similar benefits from assignment to a counselor predicted to be one standard deviation above average on a composite measure of effectiveness. Counselors also impact suspensions, AP and SAT test-taking, as well as the type of college a student attends.

Second, counselor assignment matters most for students who are low-achieving and low-income. These students are the least likely to receive college information from their parents or social networks and are also less likely to graduate high school and attend college than their peers (Hoxby & Avery, 2013; Radford, 2013). For high achieving students, counselors are primarily important for increasing college selectivity. In general, good counselors are effective at improving all measures of educational attainment; however, counselors who improve student behavior in high school tend to be different from those who increase selective college attendance. This specialization is not surprising given counselors' large caseloads and the breadth of skills required to excel at all of their duties.

Third, counselor effects on educational attainment appear driven by the information and direct assistance they provide students rather than through improved short-term skills. Counselors do not significantly vary in their effects on students' short-term cognitive skills and their effects on non-cognitive skills are not predictive of longer-term outcomes. Counselors' largest measurable effects are on college readiness and selectivity, and effectiveness on these dimensions is most predictive of students' educational attainment. This indicates that educators can influence students' long-term outcomes through channels other than short-term skills. They may increase educational attainment by providing students information about and improved access to education opportunities.

Fourth, I show that students benefit from being matched to a counselor of the same race and from having a counselor who attended a local college. Non-white students are more likely to graduate high school and attend college if assigned to a non-white counselor. Counselors who earned a bachelor's degree in Massachusetts also increase high school completion and college enrollment more than counselors educated elsewhere. This may be because locally educated counselors know more about the local college market or because they are more familiar with state graduation requirements and the needs of local students. Counselors also increase college attendance at the type of college they attended.

Finally, I provide evidence that the benefits, in terms of educational attainment, from improving access to effective counselors will likely be similar to or larger than those from reducing counselor caseloads. Consistent with research on class size, I find that students who share a counselor with more students have lower educational attainment (Angrist & Lavy, 1999; Krueger, 1999; Fredricksson et al, 2013). Much of the negative association between caseloads and student outcomes, however, disappears when I control for student or school characteristics. Using within school variation in caseloads, I find that hiring a new counselor in every Massachusetts high school will likely lead to smaller gains in educational attainment than increasing counselor effectiveness by one standard deviation.[4] Increasing access to effective counselors will also likely have effects

[4]Counselor caseloads in Massachusetts' high schools are near the national average for high schools. My analysis cannot speak to the benefits of dramatically reducing caseloads, the benefits of hiring an additional counselor in schools

similar to many successful college-going interventions and to increasing teacher effectiveness.

Broadly, this paper builds on three literatures. First, and most directly, it is related to research on counselors in other settings, such as job searching, housing assistance, and elementary school. This research shows that counseling can influence choices and important economic outcomes, such as job placement, earnings, and where individuals live (Card et al, 2010; Behaghel, Crepón & Gurgand, 2014; Bergman et al, 2019). I expand on this work by showing that publicly supported counseling in high schools can also have large effects on the choices and educational attainment of adolescents, and that there is significant variation in the effectiveness of individual counselors.

My paper provides the first quantitative evidence on how much individual school counselors impact students, how much variance exists across counselors, and the characteristics of the most effective counselors. Prior work on school counselors shows that increasing access to counselors, through smaller caseloads, improves elementary students' test scores and behavior, as well as high schoolers' four-year college enrollment (Carrell & Hoekstra, 2014; Hurwitz & Howell, 2014; Reback 2010). Supplemental after school or summer counseling for high schoolers can also increase college attendance, especially at recommended schools, but many studies find only limited effects of these programs on college enrollment and persistence (Barr & Castleman, 2019; Castleman & Goodman, 2018; Castleman, Page & Schooley, 2014; Sullivan, Castleman & Bettinger, 2019; Bettinger & Evans, 2019; Gurantz et al, 2019). The only one of these papers to estimate the effectiveness of individual counselors does so with 30 employees of an after-school program and finds little variation in counselor effectiveness, perhaps because its counselors follow a heavily standardized protocol (Barr & Castleman, 2019).

The quantitative evidence I present on counselors' causal effects confirms the narratives in the qualitative literature on school counselors. A large body of qualitative research documents the challenges faced by counselors at under-resourced schools and the potential for counselors to impact individual students' choices (McDonough, 1997; Perna, Rowan-Kenyon & Thomas, 2008; Sattin-Bajaj et al, 2018). There is also evidence that changing counseling approaches can increase college enrollment, especially for disadvantaged students (Stephan & Rosenbaum, 2013). This

with caseloads well above the national average, or benefits which cannot be measured using administrative data.

literature suggests that the time counselors spend with students may have important implications and it provides helpful context for understanding how counselors can have large effects.

Second, this paper builds on the education production function literature, as well as research on teachers and school resources, by studying an element of the production function which has received little attention. I show that school personnel beyond teachers can have large impacts on educational attainment and that demographic matches of educators and students improves student outcomes (Chetty, Friedman & Rockoff, 2014b; Gershenson et al, 2018; Jackson, 2018; Todd & Wolpin, 2003). Quasi-random assignment of counselors, large caseloads and a wide array of responsibilities also enable me to explore questions that are difficult to study in the teacher setting. I show that these workers manage their many and diverse responsibilities by specializing in certain types of rare outcomes, and that their effects on long-term outcomes are not just through their impacts on short term skills.

Assignment to a counselor who is one standard deviation above average has a similar effect on high school completion and college outcomes as does being assigned to a one standard deviation better teacher. My estimates are slightly larger than the best estimates of teachers' long-run impacts on high school completion and college attendance. Chetty, Friedman & Rockoff (2014b) find that a one standard deviation better 3rd to 8th grade teacher (in terms of test scores) increases college enrollment by .8 percentage points, and, using a broader measure of teacher effectiveness, Jackson (2018) finds that a one standard deviation better 9th grade teacher increases high school graduation and four-year college intentions by about 1 percentage point. While these are likely underestimates of teachers' true effects on educational attainment, my estimates are also slight underestimates (Chamberlain, 2013).[5] Furthermore, improving access to effective counselors may be a more cost effective way to increase educational attainment than improving teacher effectiveness because counselors often serve more students, there are far fewer counselors than teachers, and many high school counselors receive little, or no, training on college advising.

Finally, my results build on literature showing that personalized guidance can increase college enrollment and college quality by showing that the quality of the guidance matters and that coun-

[5] This is because the assignment rules are used as instruments and because I only look at the first counselor to which a student is assigned.

selors may be an important channel through which students receive such guidance (Bettinger et al, 2012; Carrell & Sacerdote, 2017; Goodman et al, 2019; Mulhern, 2019). Recent work indicates that, when scaled, low-touch informational interventions have limited, if any, impacts on college enrollment (Bird et al, 2019; Gurantz et al, 2019; Hurwitz & Smith, 2017). Higher touch interventions, especially when carried out by individuals or supported by schools, however have been shown effective in multiple settings. The type of personalized guidance provided by counselors can be similar to the high touch guidance provided by financial professionals, peer mentors, highly personalized guidance tools or siblings. On a large scale, counselors' capacity to impact trends in educational attainment may be greater than some of these interventions because nearly every high schooler has access to a counselor and students may trust counselors more than external assistance or general information.

The paper proceeds as follows. Section 2 describes background information on counselors and a theoretical framework. The data are described in section 3, and section 4 presents the methods. Section 5 describes how much counselors vary in their effects on students, and the implications of assignment to a more effective counselor. Section 6 explores the dimensionality of counselor effectiveness and specialization. Section 7 shows how counselor effectiveness varies with counselors' observable characteristics. Section 8 compares the importance of counselor effectiveness to that of caseloads, teachers and other forms of postsecondary guidance. Section 9 provides evidence from Wake County, NC on the external validity of the Massachusetts estimates. Section 10 concludes.

2 Background and Theoretical Framework

In this section, I describe how counselors spend their time and how their efforts can impact human capital accumulation and educational attainment. Then I model how their efforts relate to the education production function.

2.1 What do High School Counselors Do?

Survey results from the 2018 "National Association for College Admission Counseling" Counseling Trends Survey indicate that U.S. high school counselors spend most of their time on course scheduling, college and career advising, and general student support (Table A.1). Given the responsibilities reported in the survey, I identify four main channels through which counselors are likely to influence students' human capital accumulation and educational attainment.

1. **Cognitive Skills:** Counselors can influence students' cognitive skills by placing them in, or removing them from, classrooms where they can accumulate human capital. Most counselors are responsible for course scheduling, so they may direct students towards or away from effective teachers and AP classes. Students' courses influence skill formation, educational attainment, and earnings (Chetty, Friedman, & Rockoff, 2014b; Jackson, 2018; Smith, Hurwitz & Avery, 2017). Counselors may also remove students from classrooms through disciplinary actions. This can benefit students remaining in the classroom but may harm the long-run outcomes of the students removed (Bacher-Hicks, Billings & Deming, 2019). Finally, counselors can help students access special accommodations, such as English language services or special education, which may increase their capacity to gain skills at school.

2. **Non-cognitive Skills:** Counselors may work on improving students' non-cognitive skills, such as behavior and engagement with school, through mental health counseling, disciplinary actions, and support in dealing with the challenges of high school. Improving student behavior or removing disruptive peers can benefit the students remaining in the classroom, and increasing attendance can increase student achievement (Carrell, Hoekstra, & Kuka, 2018; Figlio, 2007; Liu, Lee & Gershenson, 2019; Goodman, 2010; Jackson, 2018). Mental health counseling may also help students gain more from their classes by increasing their capacity to concentrate in school, reducing the need for disciplinary actions or increasing attendance (Heller et al, 2017; Schwartz & Rothbart, 2019).

3. **Information:** Counselors may provide information about postsecondary education and labor market options. This could cover the costs and benefits of different options, as well

as the steps to apply to and enroll in college. Students often lack good information about these options, which can lead to suboptimal education or career choices (Hastings, Neilson, & Zimmerman, 2015; Hoxby & Avery, 2013; Jensen, 2010; Oreopoulos & Dunn, 2013). In addition, counselors may provide specific recommendations or nudges. Whether this more personalized information improves or worsens outcomes will likely depend on the guidance provided (Castleman & Goodman, 2018; Hoxby & Turner, 2015; Mulhern, 2019).

4. **Direct Assistance:** Counselors can directly influence students' high school experiences by providing individual accommodations, enforcing discipline policies, and approving graduation petitions. They can also directly influence what students do after high school by obtaining SAT fee waivers, writing letters of recommendation, and helping students complete forms and sign up for services. Counselors have considerable discretion over what they put in their recommendations; 62% of colleges place considerable or moderate importance on the counselor's letter in the admissions process (Clinedinst & Koranteng, 2017). In addition, fee waiver receipt predicts college enrollment and counselors are responsible for obtaining and distributing SAT fee waivers from the College Board (Hoxby & Turner, 2013; Bulman, 2015). Finally, counselors may assist students with college or job applications to increase students chances of successfully moving onto the next phase (Bettinger et al, 2012). Prior research suggests that this type of direct assistance may have larger effects than simple information provision (Bettinger et al, 2012; Bird et al, 2019; Gurantz et al, 2019).[6]

Counselors' roles vary considerably across schools and districts. Many schools employ specific college counselors or school psychologists. In these schools, guidance counselors may spend less time on the second and third categories. Counselors may also spend considerable time on administrative duties, which could lower their influence on students. As I discuss more in section 3, this study focuses on counselors who are likely to have responsibilities across all four domains.

[6] I separate the information and assistance channels because several papers suggest that information alone may not be enough to sway postsecondary choices.

2.2 Counselors and the Education Production Function

In the education production and value-added literatures, educators are typically modeled as affecting students' skills and long-term outcomes only through their impacts on students' accumulated ability (Chamberlain, 2013; Jackson, 2018; Todd & Wolpin, 2003). Existing models, however, ignore educators' potential effects on long-term outcomes through channels other than their influence on student ability. The previous section highlights some of the ways in which counselors, in particular, can impact students' educational attainment without influencing their ability. In this section, I expand the model typically used to show how educators influence educational attainment to incorporate their effects on students' awareness of their long-term options and their direct influence on the barriers students face in reaching these outcomes.

I treat the first two channels in section 2.1 as the ability dimension. In these ways, counselors influence students' opportunities to gain both cognitive and non-cognitive skills. The third channel encompasses counselor effects through information, such as telling students about their long-term options, the costs and benefits associated with them, and the steps needed to reach these outcomes.[7] The fourth channel is the direct assistance dimension. This encompasses actions that counselors take which directly impact student outcomes, such as creating or eliminating barriers, but which do not primarily flow through students like the other dimensions.

Students arrive in high school with endowments ν_i. Following Jackson (2018), I allow for the vector of endowments to be multidimensional. It may include components for students' initial cognitive ν_{ci} and non-cognitive abilities ν_{ni}, their knowledge of the returns to school and the college enrollment process ν_{ki}, as well as the assistance they receive from their social networks ν_{di}.

$$\nu_i = (\nu_{ci}, \nu_{ni}, \nu_{ki}, \nu_{di}) \tag{1}$$

Educator j's quality is represented by the vector ω_j. Educator quality is multidimensional since one's effectiveness at improving cognitive skills may differ from one's impacts on non-cognitive

[7] One could think of knowledge about career and postsecondary options as a dimension of ability. I treat it as a separate dimension because this knowledge is usually unrelated to one's human capital and is generally not useful in the labor market. It is also a dimension that would be irrelevant under perfect information.

skills or college knowledge. They can also have direct influence ω_{dj} over some outcomes.

$$\omega_j = (\omega_{cj}, \omega_{nj}, \omega_{kj}, \omega_{dj}) \tag{2}$$

Students can have differential responsiveness to educator effectiveness.[8] This responsiveness is represented by the matrix D_i.

$$D_i = \begin{pmatrix} D_{ci} & 0 & 0 & 0 \\ 0 & D_{ni} & 0 & 0 \\ 0 & 0 & D_{ki} & 0 \\ 0 & 0 & 0 & D_{di} \end{pmatrix} \tag{3}$$

The quality of educator j for student i is $\omega_{ji} = D_i\omega_j$. In models of teacher value-added, a student's ability is $\alpha_{ij} = \nu_i + \omega_{ij} + \phi_{i-j}$, where ϕ_{i-j} is the impact of all other educators on the student's ability (Jackson, 2018). In the case of counselors, however, some dimensions of their effectiveness are unrelated to student ability. Thus, I split the vector of educator effectiveness into three pieces and model how each of these pieces is related to educational attainment.

First, counselors may impact ability, similar to teachers. Following Jackson (2018), I model educators as impacting ability through cognitive and non-cognitive dimensions. Thus, a student's ability is $\alpha_{ij} = \nu_{ci} + \nu_{ni} + D_{ci}\omega_{cj} + D_{ni}\omega_{nj} + \phi_{i-j}$.

Counselors can also impact students' long-run outcomes by providing them information. This information can change whether and where students enroll in college, but it does not directly increase their ability. Let γ_{ij} represent student i's awareness of the returns to school and knowledge about the college enrollment process. Then, $\gamma_{ij} = \nu_k + D_{ki}\omega_{kj}$.

Finally, educators may directly influence student outcomes by creating or reducing barriers to success. Let ψ_{ij} represent educator j's direct influence on outcomes, through channels such as letters of recommendation or enforcement of school discipline and graduation policies. Endowments on this dimension may reflect the assistance provided by others in a student's social network. The

[8] This may be because some students know a lot about college and the returns to school from their parents or because they take steps to get themselves into the best classes.

importance of the counselor's effectiveness, D_{di}, may depend on the student's characteristics.[9] Then, $\psi_{ij} = D_{di}\omega_{dj}$.

Putting all of this together, student i's long-run outcome Y_{lij} is a function of her ability, knowledge and direct assistance, and the importance of each dimension for the relevant outcome.

$$Y_{lij} = \beta_l \alpha_{ij} + \Gamma_l \gamma_{ij} + \delta_l \psi_{ij} + \epsilon_{ijl} \equiv (\nu_i + \omega_{ij} + \phi_{i-j})^T \begin{pmatrix} \beta_l \\ \Gamma_l \\ \delta_l \end{pmatrix} + \epsilon_{ijl} \tag{4}$$

The coefficients, β_l, Γ_l, δ_l are analogous to a price vector, showing how ability, college knowledge, and direct assistance are related to high school completion or college enrollment. For example, β_l indicates how a student's ability impacts the student's outcome Y_l. These coefficients do not depend on counselors. ϵ_{ijl} is a random error term.

Educator $j's$ effect on outcome Y_l, is the sum of her effects on each dimension, weighted by the importance of each dimension for the outcome. Formally, the average effectiveness of counselor j on outcome Y_l is

$$\theta_{lj} = E[\omega_{ij}](\beta_l \;\; \Gamma_l \;\; \delta_l)^T \tag{5}$$

Previous studies have assumed that educator effects on Y_{lij} are only through the ability dimension ($\beta_l \alpha_{ij}$), meaning that educators either have no effects on the other dimensions, or the importance of these dimensions is zero. Formally, their assumption is that that $E[\omega_{kij}]\Gamma_l = 0$ and $E[\omega_{dij}]\delta_l = 0$. I expand on existing models of educator effects by enabling educator effects to be a weighted average of their impacts on ability α_{ij}, college knowledge γ_{ij}, and the direct assistance they provide ψ_{ij}. If $E[\omega_{kij}]\Gamma_l \neq 0$ or $E[\omega_{dij}]\delta_l \neq 0$, then educators impact students' long-run outcomes through channels other than their effects on student ability.

In section 5.2.2 I show evidence that counselors explain meaningful variation in student outcomes that is unrelated to their effects on students' (measured) ability. Formally, I show that $\theta_l \neq 0$ but $\beta_l = \mathbf{0}$. Thus, educators can influence educational attainment and labor market opportunities

[9] For example, the counselor's adherence to discipline policies will only matter for students with disciplinary infractions. Similarly, college recommendation letters only matter for students who apply to college.

by doing more than just impacting students' skills. They can also influence outcomes by providing information and modifying barriers to them. These channels of the education production function may also apply to teachers.

3 Data

I use student-level data from the Massachusetts Department of Elementary and Secondary Education. They provided data on student demographics, courses, grades, attendance, discipline and standardized test scores. These data have been connected to National Student Clearinghouse records on postsecondary enrollment and degree completion for students projected to graduate high school between 2008 and 2017. My sample is limited to the students and counselors I can link based on quasi-random last name assignment policies.

Many school districts and state agencies, including Massachusetts, do not maintain student-counselor linkages in their databases. It is, however, common practice to post counselor assignments on school webpages when the school uses a simple assignment mechanism. This is done so that parents and students can easily find and contact their counselor. In Massachusetts, about a third of public high schools assign students to counselors based on the beginning letters of their last name, and many schools posted the assignments on their webpages for at least a few years between 2004 and 2018. National survey data indicate that over 50% of schools assign counselors to students based on their last name (High School Longitudinal Study, 2009).[10]

I reviewed the archives of school counseling websites for all high schools in Massachusetts between 2004 and 2019 to determine which schools used last name assignment rules in which years. When available, I collected the assignment rules from the websites and used them to determine which counselor each student would have been assigned to based on his or her last name. The assignment rules are adjusted slightly from year to year based on changes in the distribution of last names or in the size of the student body, but most counselors serve the same region of the alphabet the entire time they work in a school.[11] In most schools, students are assigned the same

[10]Conversations with school counselors indicate that schools like this approach because of its simplicity. It is simpler to implement and more transparent than random assignment, and seems fairer to them than purposeful matching.

[11]Over the years I observe, the average counselor in my data shifts the letter where their assignments start by less

counselor for 9th-12th grades. In a few schools, students on the edge of an assignment rule may switch counselors between grades to help even caseloads.

Among Massachusetts' 393 public high schools, I identified 143 which used a last name assignment rule in at least one year between 2007 and 2017.[12] Many of the remaining schools did not post any policy, some assigned students to counselors by grade, others assigned students by their track or program, and some schools only had one counselor.[13] I restrict my sample to the 131 schools which had last name assignment rules posted for at least two cohorts. Table A.2 compares the high schools in my sample to those excluded. My sample is over-representative of suburban schools and under-representative of urban schools in the state. This is, in part, because very few Boston schools posted last name assignment rules.[14] The schools in my sample tend to be whiter and have fewer low-income students than the state, but the average per-pupil spending is slightly lower than the schools excluded. My sample mainly consists of traditional high schools but also includes a few charter and vocational schools.

On average, I observe assignments for 5 cohorts in each school with a posted last name policy. Many schools were missing archives of their webpages for a few years so assignments could not be verified in every year. For this reason, I impute some assignments and focus on the first counselor linked to each student.[15] Including the years of imputed assignments increases the average duration a school is in my sample to 7 cohorts.

I link 154,905 students (out of 819,268) to 723 counselors. For the estimates of individual counselor effects, I focus on the 142,161 students, 510 counselors, and 131 schools for which I can link counselors to at least two different cohorts with at least 20 students in each cohort.[16] In section 7, when showing how counselor characteristics are related to student outcomes, I do not require a counselor to serve multiple cohorts in order to be included. In section 8, when computing the rela-

than three letters; 52% of counselors do not change their starting letter and 52% do not change their ending letter.

[12] An additional 19 schools posted a last name assignment rule in 2018 or 2019.

[13] Schools which did not post any policy could still have used a last name assignment policy. Nationally, assignment by grade and random assignment are common alternatives to the last name policy. If counselors are randomly assigned, it is unlikely that the school would post anything about the assignments online.

[14] Many Boston schools also only have one guidance counselor and a separate college counselor.

[15] The imputations use the consistency in the assignments over time, and data on the years a counselor was employed in a school, to determine which counselor a student was likely to be assigned to during each year at the school.

[16] These restrictions help to improve the precision of my estimates and enable me to construct leave-year-out estimates for counselor effectiveness.

tionship between caseloads and student outcomes, I use all Massachusetts high schoolers enrolled at a school with reasonable counselor FTE measures (between 2005 and 2017).[17] Table 1 compares the sample of students used in each of these sections.

Massachusetts provided Human Resources (HR) data on counselors' employment, education and demographics. There are some counselor assignments which I could not link to the HR records (based on the counselor's name). I include these counselors in my main sample but they are excluded from analyses requiring background information on the counselor. Table 2 describes the counselors in the HR databases and in my sample. I link 74% of counselors to the HR data. Table 2 also describes the 19% of counselors who self-reported their education data.

I focus on the first counselor assigned to a student based on the student's last name to avoid endogeneity in assignment duration. Most counselors are intended to serve students for four years. Assignment duration may be endogenous if counselors leave during a student's high school career because they are assigned particularly challenging students. Table 2 shows that the average counselor in my sample is matched to 184 students each year and 61 students per grade.[18] The average counselor is matched to 4.5 cohorts and students are matched to an average of 1.1 counselors.

Table 1 indicates that the students matched to counselors are slightly less diverse and higher achieving than the average Massachusetts student. Some of the positive selection could be driven by higher resource schools having nicer websites with easy to find assignment rules.[19] In addition, many high schools have separate counselors for students with limited English proficiency or those enrolled in career and technical education. Since the last name assignment mechanism does not apply to them, these students are often dropped from my sample. The exclusion of many Boston schools also probably explains why my sample is less diverse than the state as a whole.

Most of the data are available for the full sample period. The main exceptions are that course

[17]For the caseload estimates, I exclude the schools which report less than .5 counselor FTEs. I use all schools for these estimates to increase my power to detect caseload effects. It is difficult to detect effects in the sample of schools for which assignments are available because I only use within school variation in caseload size. Similarly, dropping the two cohort restriction for the analyses in section 7 increases my power.

[18]Counselors may have slightly larger caseloads, since there are some students I cannot match to counselors. This is usually because the student's last name is missing or because some students, such as English language learners or special education students, are assigned separately from the last name assignment mechanism.

[19]The districts in my sample do not have higher per pupil spending than the excluded districts (but these averages mask some differences in spending by grade and student need).

performance data are only available since 2012 and 10th grade state test scores are not available for the class of 2017.[20] Bachelor's degree completion is also only available for students graduating high school prior to 2013 and college persistence rates are not available for the class of 2017.

In Massachusetts, there are no regulations around caseload sizes or counseling duties. The average caseload in high schools is 285 students, which is close to the national average. Massachusetts also requires all schools to have a school adjustment counselor. These counselors primarily support the mental health, social, and emotional needs of students, freeing up time for the guidance counselors to focus more on academic support. Massachusetts provides a recommended counseling model, and it requires licenses and Master's degrees to be a guidance counselor.[21] The recommended counseling model consists of guidelines around how to provide counseling services and may be adopted by individual schools, but it is not required. The state also has a formal evaluation processes for counselors but there exists little variation in the evaluation scores.

Some U.S. high schools have college counselors who are separate from guidance counselors. These counselors are most common at high income and private schools, though low-income schools may receive college counseling services from national organizations, such as College Advising Corps (Clinedinst & Patel, 2018). For the most part, college counselors are not in the schools in my sample. This may be because the schools which delineate counselor roles are less likely to have multiple guidance counselors, or to assign them to students based on students' last names (Clinedinst & Patel, 2018).[22] The effects of guidance counselors on educational attainment may be different in schools with specific college counselors or different counselor responsibilities.

4 Methods

Students in my sample are assigned to counselors based on their school, cohort and last name. I use the quasi-random variation in counselor assignments, generated by these assignment rules, to

[20]The state changed the test administered to students in 2015. Because it is difficult to concord the test scores across different tests and years I exclude the new test scores for the 10th graders in 2015.

[21]Counselors can earn their license by receiving a degree from an accredited counseling program, working in schools with a licensed supervisor for 450 hours and passing the National Counseling Exam plus a basic literacty and communications test.

[22]For instance, some public high schools in Boston only have one guidance counselor, but, they also tend to have a College Advising Corps member, a school adjustment counselor, and a school psychologist.

causally identify the impact of individual counselors on student outcomes. I use the assignment rules as instruments and control for the assignment mechanism. Thus, I compare outcomes for students who attend the same school but who are assigned to different counselors because of their last name. Since students with A last names may have higher potential outcomes than students with Z last names, I use first letter of last name fixed effects to subtract off statewide differences common to the first letter of last name. I also include statewide cohort fixed effects to account for secular trends. Grade fixed effects capture differences in students who enter my sample at different points. I report reduced form estimates since I cannot observe if students did not follow their assignment.[23]

The key identifying assumption is that, conditional on the first letter a student's last name, cohort, grade, and school, students' potential outcomes are constant across counselors. To further alleviate concerns of student sorting, I control for students' eighth grade test scores, demographic indicators, and indicators of services received in eighth grade.[24] My results are robust to including first letter of last name fixed effects interacted with ethnicity, achievement levels or urbanicity. After introducing the methods, I show placebo tests which indicate no evidence of sorting to counselors by eighth grade test scores.

Since assignment is quasi-random, the average outcomes of counselor j's students, conditional on the controls, should be an unbiased estimate of counselor j's impact on her students. Thus, counselor effects μ_j can be estimated by ordinary least squares.

$$Y_i = \alpha + \mu_j + \beta X_i + \nu_n + \delta_s + \gamma_g + \psi_t + \epsilon_i \tag{6}$$

This approach yields a fixed effects estimate, $\hat{\mu}_j$, for each counselor. Each student, i, is assigned to one counselor and is part of one cohort so, for simplicity, i refers to (i, j, t). The control variables

[23] This means that I likely underestimate the true effects of counselors on students.

[24] The full set of controls includes race, gender, English language learner status, special education status, receipt of title 1 services, existence of a 504 plan, free-and-reduced price lunch status, eighth grade attendance, enrollment in a Massachusetts public school in 8th grade and indicators for taking the eighth grade tests. Missing values are coded as zeros to preserve the sample size and indicators for missing variables are included as controls. Most students missing values were not enrolled in a public school in Massachusetts in 8th grade, so the enrollment variable picks up any ways these students are, on average, different. I focus on students' scores, attendance and services received in eighth grade since counselors may affect their access to services in high school.

are represented by the vector X_i and fixed effects are included for each student's school δ_s, grade γ_g, cohort ψ_t, and first letter of last name ν_n. ϵ_i is a random error term.

While $\hat{\mu}_j$ is an unbiased estimate of a counselor's causal effect, it is not an optimal out of sample predictor of a counselor's effectiveness because it contains considerable noise. This noise also means that the variance of these estimates will be an upward biased estimate of the true variance of counselor effects. To address these concerns, I use a model based approach to estimate the variance of counselor effectiveness. Then, I use these variance estimates to generate empirical Bayes estimates which shrink the estimates towards the mean (of zero) based on their reliability.

4.1 Estimating the Variance of Counselor Effects

First, I estimate how much variation exists in counselor effects on student outcomes. Multiple approaches for estimating this variance have been used in the literature. Following Kraft (2019) and Jackson (2019), I directly estimate this variance via restricted maximum likelihood using a model-based approach. This approach produces a maximally efficient and consistent estimator for the true variance of counselor effects. My results are very similar if I instead use the covariance based approach from Kane & Staiger (2008).

I fit the following mixed effects model with counselor random effects and the same fixed effects and controls from equation 6. The main difference between this equation and equation 6 is that counselor effects are treated as random. This allows me to directly estimate their variance. I also include a cohort random effect , ϕ_{jt}, nested within counselors, to capture year to year fluctuations in counselor effectiveness. This means that μ_j will capture the time-consistent dimension of counselor effectiveness.

$$Y_i = \alpha + \mu_j + \phi_{jt} + \beta X_i + \nu_n + \delta_s + \gamma_g + \psi_t + \epsilon_i \tag{7}$$

Uncovering the variance of μ_j using this model and restricted maximum likelihood estimation requires the assumption of joint normality. Under this assumption, I will obtain maximally efficient and consistent estimates for the variance of counselor effects and student level disturbances.

This model also assumes that the variance attributable to counselors is orthogonal to the residual student variance.

4.2 Empirical Bayes Estimates of Effectiveness

Next, I construct empirical Bayes estimates of counselor effectiveness. I fit the mixed effects model in equation 7, which shrinks the counselor effects $\hat{\mu}_j$ towards the mean (of zero) based on their reliability. The reliability of $\hat{\mu}_j$ depends on the within and across counselor variance, as well as the number of students, n_j, assigned to the counselor. The empirical Bayes estimates are:

$$\hat{\mu}_j = \bar{\mu}_j \frac{\hat{\sigma}_\mu^2}{\hat{\sigma}_\mu^2 + (\sum_t (1/(\hat{\sigma}_\phi^2 + (\frac{\hat{\sigma}_\epsilon^2}{n_{jt}})))^{-1}} \tag{8}$$

$\hat{\sigma}_\mu^2$ is the estimated variance of counselor effectiveness from section 4.1. The variance of the residual, $\hat{\sigma}_\epsilon^2$, and the counselor by cohort shocks, $\hat{\sigma}_\phi^2$, are also directly estimated in the model from equation 7. n_{jt} is the number of students assigned to counselor j in each year t. I restrict my sample to counselors assigned to at least two cohorts with at least twenty students per cohort.

I construct estimates of counselor effectiveness, $\hat{\mu}_j$, for a variety of high school and college outcomes. Given the many outcomes that counselors may impact, I also group student outcomes into indices to measure counselor effects on a few main dimensions. The five main indicecs and their components are listed below. I construct each index using the weights from principal components analysis and I standardize them to have a mean of zero and standard deviation of one in the full population of Massachusetts high school students.[25]

1. Cognitive Skills	2. Non-Cognitive Skills	3. College Readiness	4. College Selectivity	5. Educational Attainment
High School GPA	Ln(Absences +1)	Took SAT	Graduation Rate (6-Years)	Graduate High School
Classes Failed	Ln(Days Truant +1)	Max SAT	Selective	Attend College
10th Math Test	Ln(Days Suspended +1)	Took an AP Test	Highly Selective	Attend Four-Year College
10th Reading Test	High School Dropout		Mean College Income	

[25] I take the log of absences, days truant and days suspended to deal with a small number of students who miss many days. To deal with zeros for these values, I take the log of the value (e.g. absences) plus one. Truancy is the same as an unexcused absence. Students who do not attend college have a value of zero for the selectivity measures and college graduation rate. For students who do not attend college, the mean income value is based on the U.S. average for individuals who do not attend college, as reported in Chetty et al (2017). For those attending college, this is the average income of students who attended their college as reported in Chetty et al (2017). College attendance is based on attendance within six months of graduating high school. The cognitive skills index is only based on 10th grade math and reading test scores for students who are in cohorts for which course data are unavailable. It is missing for the class of 2017 since test data are unavailable for them.

The first two indices, for cognitive and non-cognitive skills, map directly to the channels for counselor effects described in section 2. The college readiness and selectivity indices are related to the information and direct assistance channels. These indices capture outcomes, such as SAT taking and the type of college a student attends, which are likely to be influenced by the information a counselor provides about college options or assistance in the application process. I use these indices to test the model in section 2. The fifth index captures counselors' direct effects on students' long-term educational attainment. Finally, I create a composite measure of effectiveness based on all five of these indices. This index is useful for showing a counselor's average effectiveness across a variety of dimensions.

Next, I construct estimates which can be used to predict the impact of assignment to a one standard deviation better counselor on a student's outcomes. To avoid mechanical endogeneity when predicting the impact of a counselor on students in year t, the students from year t should be excluded from the estimate for that counselor's effectiveness. Following Chetty, Friedman & Rockoff (2014) and Jackson (2018), I construct leave-year-out (jackknife) measures of counselor effects, $\hat{\mu}_{j-t}$. I use these leave-year-out measures to identify the components of counselor effectiveness which persist over time, and to explore the dimensionality of counselor effectiveness.

These leave-year-out estimates $\hat{\mu}_{j-t}$ are constructed in the same manner just described for $\hat{\mu}_j$, except students from year t are excluded at each step. For each year t and outcome I compute $\hat{\mu}_{j-t}$ and standardize the values.[26] Then I use the counselors' estimated impacts on the indices or outcomes to test whether the out of sample estimate predicts student outcomes as expected. These estimates also show the effects of assignment to a counselor who is predicted to be better on a particular dimension.

$$Y_i = \alpha + \psi\hat{\mu}_{j-t} + \beta X_i + \nu_n + \delta_s + \gamma_g + \psi_t + \epsilon_{iy} \tag{9}$$

Standard errors are clustered by counselor and year. I use the same student-level controls and fixed effects as in the construction of the empirical Bayes estimates. I also use this specification to test the relationship between counselor effects on students' short-run and long-run outcomes.

[26]They are standardized using the standard deviations computed in section 4.1 and reported in Table 3.

4.3 Placebo Tests

I find no evidence of sorting to counselors by eighth grade test scores. Panel (A) of Table 3 shows that counselor assignment explains no variation in students' eighth grade test scores, conditional on all controls except for the eighth grade tests. Similarly, counselors explain no variation in either 8th grade math or reading scores.

Figure A.1 shows that, conditional on all controls except for eighth grade achievement, students with higher test scores are not assigned to counselors who are better at increasing high school graduation or college enrollment. Formally, this figure shows the relationship between a counselor's leave-year-out effectiveness and the eighth grade test scores of students in the left-out year. I use the leave-year-out estimates because one would expect college enrollment rates to be higher in the year that a counselor happens to get more high achieving students. Table A.3 shows the placebo tests for the main measures of effectiveness.

5 Counselor Effectiveness

5.1 Magnitude and Variance of Counselor Effects

Figure 1 and Panel (B) of Table 3 show that, within schools, counselors significantly vary in their effects on educational attainment.[27] The standard deviation of counselor effects on high school graduation is 2 percentage points and it is 1.7 percentage points for four-year college attendance. The standard deviation for college persistence is 1.1 percentage points. This means that students assigned to a counselor who is one standard deviation above average (on this metric) are 1.1 percentage points more likely to persist in college. Randomization inference (Table A.5) indicates that my estimates are significantly larger than those expected due to chance.[28]

Panel (C) of Table 3 shows that counselors also impact what students do in high school. Assignment to a one standard deviation better counselor (in terms of SAT taking) increases a student's

[27]Another common approach employed in the teacher setting is to use the covariance of an educator's fixed effect over time as a measure for the true variance of educator effects. Results using the covariance based approach are similar and can be seen in Table A.4.

[28]Table A.5 contains results based on randomization inference (following Athey and Imbens (2017)) where the variance of counselor effects are estimated using iterations of randomly re-assigned counselors.

probability of taking the SAT by 4.2 percentage points. Counselors also influence AP test taking but they do not significantly vary in their effects on students' GPAs or 10th grade test scores. In addition, I find no significant variation in counselor effects on attendance or unexcused absences. There is, however, significant variation in their effects on suspensions. Students assigned to a counselor who is one standard deviation below average are 2.8 percentage points more likely to be suspended than students assigned to the average counselor. Thus, counselor assignment can be an important determinant of students' high school experiences.

Panel (D) of Table 3 shows that counselors influence the types of colleges that students attend. Counselors vary in their influence on whether a student attends a selective college, the graduation rate at the college a student attends, as well as whether the student majors in a STEM field. The standard deviation of counselor effects on college quality, as measured by the average earnings of the students who attended the college (from Chetty et al, 2017), is $445. Counselor effects on where students attend college may influence their probabilities of earning a college degree and their future earnings (Cohodes & Goodman, 2014; Hoekstra, 2008).

Finally, ninth grade counselors have larger effects on high school graduation than counselors in later grades, while 12th grade counselors have the largest effects on four-year college enrollment and the graduation rate of the college a student attends (Table A.6).[29] The appendix contains more details on the variance estimates and their components (Tables A.7 and A.8). In addition, covariance based estimates of the variance are in Table A.4.

5.2 Leave-Year-Out Estimates

5.2.1 Impacts of a Better Counselor

Next, I construct leave-year-out empirical Bayes estimates, $\hat{\mu}_{j-t}$, to show the impact of being assigned to a counselor who is predicted (based on other students) to be one standard deviation above average. These estimates also show that a counselor's level of effectiveness persists over time and is a valid out of sample predictor. Panels (A) and (C) of Figure 2 show that a counselor's

[29] These estimates come from variation in the duration of counselor assignments. 9th grade counselors may be different from 12th grade counselors if students' counselors leave while they are in high school or if the high school hires an additional counselor.

predicted effectiveness, in terms of high school graduation or four-year college attendance, is predictive of the relevant outcome. Panel (A) of Table 4 indicates that, for high school graduation and college attendance, the 95% confidence interval of the predicted effect contains one. Panel (B) of Table 4 shows that a one standard deviation improvement in a counselor's predicted effectiveness on four-year college attendance increases students' four-year college attendance by 2.3 percentage points. A similar effect is apparent for high school graduation and any college attendance.

Next, I construct a composite measure of counselor effectiveness to identify what it means for a student to be assigned to a one standard deviation better counselor. The construction of this index is described in section 4. It defines "better" more broadly than the previous measures which just look at a counselor's effectiveness in terms of one outcome. Panels (B) and (D) in Figure 2 show that the composite index of effectiveness predicts high school graduation and four-year college enrollment rates to a degree similar to the outcome-specific measures of effectiveness. Panel (A) of Table 5 indicates that the composite index is predictive of all my measures of educational attainment. A one standard deviation better counselor in terms of this index increases high school graduation by 2 percentage points and four-year college enrollment by 1.7 percentage points.

The positive relationship between the composite index and the measures of educational attainment indicate that, in general, counselors who are effective at increasing high school graduation are also effective at increasing college attendance and persistence. The composite index also contains less measurement error than the other measures of effectiveness (Table A.8).

Next, I show that counselor effects are much larger for low-achieving and low-income students.[30] Figure 3 shows the relationship between a counselor's predicted effectiveness, in terms of the composite index, and high and low achieving students' high school graduation and four-year college enrollment rates. It indicates that counselor effectiveness is more predictive of low-achieving student outcomes than those for high achievers. Panel (A) of Table 6 reports that a one standard deviation better (predicted) counselor, in terms of the composite index, increases high school graduation for low-achieving students by 3.4 percentage points and college attendance by 2.5 percentage points. A similar pattern is apparent for four-year college attendance and college

[30]Low-achieving refers to students with eighth grade test scores below the state average. High achieving refers to students with eighth grade test scores above the state average.

persistence. These increases represent an 8% increase in four-year college attendance and a 6% increase in persistence for low-achieving students. Counselors have no significant effects on these outcomes for higher achieving students. The only outcome on which counselors have similar effects for students of different achievement levels is the graduation rate of the college a student attends. This may be because there is more room to change the quality of the college a high achieving student attends than the decision of whether to attend college. 83% of high achieving students attend college compared to 50% of low-achieving students, but the average graduation rate of the college attended by high achieving students is only 56%.

Panels (B) and (C) of Table 6 also indicate that counselor effectiveness matters more for low-income (FRPL) and non-white students than for their peers. Low-income students assigned to a one standard deviation better counselor are 3.4 percentage points more likely to graduate high school than students assigned to an average counselor. Similarly, they are 2.2 percentage points (8%) more likely to attend a four-year college. The differences for non-white and white students are not statistically significant at the 5% level; however, the point estimates of counselor effects on non-white students' high school graduation and college enrollment are all larger than their effects on white students.

Counselors' large effects on low-income and low-achieving students are important because these students are most likely to be on the margin of completing high school and attending college. Low-income students are also less likely to have access to social networks with college information and other resources to help them access college (Hoxby & Avery, 2013). Furthermore, these results indicate that counselors may be an important resource for closing socioeconomic gaps in education.

I find only small differences in counselor effects across males and females (Table A.9). None of these differences are significant at the 5% level, which contrasts the large gender differences found by Carrell & Sacerdote (2017) in student responsiveness to peer college mentoring. Similarly, I find that counselors have similar effects in rural, suburban, and urban areas. Finally, counselor effects on high school graduation and college attendance appear concentrated among the lowest achieving students.[31] Their effects on four-year college attendance and college graduation rates are similar for middle- and low-achieving students.

My results are similar when I use the methods described by Kane and Staiger (2008) or Chetty, Friedman & Rockoff (2014) to estimate educator effects. Results based on these approaches are in Tables A.10 and A.11. They are also similar with a logit specification (Table A.12).

5.2.2 Channels of Counselor Effects

Next, I explore the channels of counselor effects described in section 2 and show how these are related to student educational attainment. I create four indices of short-term counselor effectiveness which map to the four channels in section 2. The cognitive and non-cognitive skills indices map directly to the channels described in section 2. In practice, I cannot distinguish between counselor effects through information and direct assistance. I do, however, observe several outcomes which are likely to be related to these channels. These outcomes include SAT and AP test taking, SAT scores, and the type of college a student attends. I group these outcomes into college readiness, and college selectivity indices, as described in section 4.

Column (5) of Table 4 shows that there is little variation in counselor effects on students' cognitive skills. This is supported by the results in Table 3 which show that counselors do not vary in their influence on GPAs or 10th grade test scores. The remaining columns of Table 4 show that counselors significantly vary in their effects on non-cognitive skills, college readiness, and college selectivity, and their effects are valid out of sample predictors of the same outcomes.

Figure 4 shows that counselor effects on educational attainment are primarily through their impacts on college readiness and selectivity. This figure reports the relationship between students' educational attainment and their counselors' predicted effectiveness in terms of cognitive skills, non-cognitive skills, college readiness and college selectivity. Effectiveness in terms of college readiness and college selectivity are the most predictive of whether students graduate high school and attend college. For most outcomes, counselors' short-term effectiveness in terms of cognitive and non-cognitive skills is not significantly related to students' educational attainment.[32]

[31] Formally, students with test scores in the bottom 3rd of my sample.

[32] In a few instances, a counselor's effect on cognitive skills is negatively related to educational attainment. This may

These results indicate that counselors' largest effects are through channels other than the ability dimension. They support the model in section 2.2 by showing that counselors influence educational attainment by doing more than just affecting students' short-term cognitive and non-cognitive skills. Counselor effects on cognitive skills are quite small and effects on cognitive and non-cognitive skills are unrelated to effects on educational attainment.[33] Counselors do, however, have significant effects on educational attainment, so their effects must be through some other channels, such as information or direct assistance. The college readiness and selectivity indices capture some ways in which counselors may provide information or assistance. For instance, counselors may have large effects on SAT taking because they provide information about when to take the test or because they obtain fee waivers for students.[34] More broadly, these results indicate that educators can have important effects on students' long-term outcomes by providing them information or helping them access opportunities.

6 Specialization

In this section I show that some counselors appear to specialize in the student outcomes they achieve. School counselors are workers who face a complex task. They are charged with achieving many outputs with a diverse set of inputs. The outputs they are responsible for range from course schedules to high school graduation and college enrollment. They are also expected to impact many intermediate outcomes and it may be difficult for them to attain all desired outcomes given their large caseloads and limited training on things like college advising. There also unclear incentives for achieving many of these outputs.

I explore how counselors manage tradeoffs in the outcomes they help produce by measuring the extent to which counselor effectiveness is unidimensional versus specialized. Theory predicts that workers will specialize in their skills and trade with one another to achieve maximum production (Rosen, 1983). Specialization occurs in many fields but most studies of it rely on formal classifications (Epstein, Ketcham & Nicholson, 2010; Garicano & Hubbard, 2008; Righi & Simcoe,

just be due to noise since the standard deviation of counselor effects on cognitive skills is quite small.

[33]This is also true when I regress student outcomes on the indices one at a time in Table 7.

[34]Counselors' impacts on SAT taking is significantly related to their effect on college attendance.

2019). For instance, doctors can pick which patients to see or firms can choose which tasks to assign to which workers. School counselors are an interesting setting to study worker specialization because they face complex tasks and have a lot of discretion over which outputs to produce and how to produce them.

6.1 Correlation of Effectiveness Measures

First, I show that counselors' effectiveness for some of the more rare outcomes are not very correlated, indicating that effectiveness is probably not unidimensional. I regress student outcomes from year t on the leave-year-out empirical Bayes estimates ($\bar{\mu}_{j-t}$) of counselor effects for other indices and individual outcomes. I follow this approach, rather than showing the correlations between a counselor's effectiveness on two different dimensions, to deal with the mechanical correlation one finds when two effectiveness measures are based on the same students.

Panel (A) of Figure 5 shows a scatterplot of counselors' leave-year-out effects for high school graduation and their impacts on the left-out students' four-year college attendance. In general, the counselors who are effective at improving high school graduation are also effective at increasing college attendance. This positive correlation may not be surprising since students must graduate high school to attend college. If, however, we expect marginal high school graduates to not be marginal college attendees, it suggests that effective counselors are good at increasing educational attainment on two different margins for different students. The graph also indicates that some counselors who are good at increasing one type of educational attainment are not good at the other. Table 7 indicates that a counselor who is one standard deviation above average at increasing high school graduation increases four-year college attendance by 1.2 percentage points. This is smaller than the effect of a one standard deviation better counselor in terms of four-year college attendance (2.3 percentage points), so effectiveness on one dimension does not necessarily translate to effectiveness on the other one.

Next, I show that counselors who improve non-cognitive skills tend to be different from those who increase selective college attendance. Panel (B) of Figure 5 shows a scatterplot of leave-year-out counselor effectiveness measures for non-cognitive skills and counselor impacts on college selectivity for the left-out students. The relationship between these two measures of effectiveness is quite small and there are many counselors who are above average on one dimension but below average on the other. Panel (B) of Table 7 indicates that a counselor's predicted effectiveness at improving non-cognitive skills is not significantly related to their effect on college selectivity (or college attendance). Thus, counselor effectiveness across these two outcomes, which probably require different skill sets, does not appear unidimensional.

The relationships between additional measures of effectiveness and student outcomes can be seen in Table 7. Effectiveness appears to translate across most measures of educational attainment. Most measures of effectiveness, however, are not predictive of students' cognitive skills, perhaps because counselors have little effect on these. Finally, the lower triangle of Table A.13 contains the correlations of the main effectiveness measures based on all students. Nearly all of the measures are positively correlated, but most correlations are not large and some of the positive correlations may be because the same students are included in all the measures.[35] These estimates also indicate that counselors who effectively improve cognitive and non-cognitive skills tend to be different from those who increase selective college attendance. These are very different outcomes so it seems reasonable that skills on one dimension would not necessarily translate to the other.

6.2 Formal Test of Specialization

Next, I formally test whether counselors specialize in the outcomes they improve. Worker specialization is typically measured by comparing workers' task composition to random assignment of tasks (Epstein, Ketcham & Nicholson, 2010; Righi & Simcoe, 2019). Workers are defined as specialists if they focus more on some tasks than is expected under a normal distribution or random assignment of tasks. The analog in this case is to compare the outcomes a counselor attains to those expected given the counselor's average quality if the counselor was equally focused on all outcomes. Specifically, does an average counselor improve all outcomes roughly equally, or do they achieve this level of "quality" by increasing some outcomes a lot and ignoring others?

To test this, I use my composite index as a measure of average counselor effectiveness. Then,

[35]Some of the low correlations could be from measurement error in effectiveness estimates. Disattenuating the correlations based on the reliability estimates in table A.8 increases the correlations but does not change the main narrative.

for each counselor and outcome, I test if effectiveness on the individual outcome is significantly different from average effectiveness. Under the null hypothesis of no specialization, a counselor's impact on individual outcomes will not significantly differ from his or her average effectiveness.

$$H1_0 : \Delta_z = (\mu_{overall} - \mu_{outcome_z})^2 = 0 \tag{10}$$

I can also measure relative specialization by comparing a counselor's effectiveness on two different outcomes. Under the null hypothesis of no specialization, a counselor's effectiveness will be the same for both outcomes.

$$H2_0 : \delta_{xz} = (\mu_{outcome_x} - \mu_{outcome_z})^2 = 0 \tag{11}$$

I test these hypotheses using the effectiveness estimates from section 5 to construct Δ_x and δ_{xz}. Then, I use a chi-square test to determine if the differences are significantly different from zero. This method been used to test the dimensionality of teacher effects (Jackson, 2018; Kraft, 2019).

The first row of Table A.13 shows that there are significant differences in a counselors' average effectiveness and their effectiveness for non-cognitive skills, cognitive skills, and highly selective college attendance. Thus, counselors appear to specialize, especially over the outcomes that apply to students at the tails of the achievement or engagement distribution.

The remaining rows in the upper triangle of Table A.13 test the second hypothesis. They also indicate that counselors who improve non-cognitive skills tend to specialize in this area. College readiness effectiveness is the measure most related to the others. This may be because the skills it requires are related to both increasing high school achievement (and behavior) as well as to increasing college attendance. Counselors who increase highly selective college attendance also tend to be different from those who improve the other outcomes. The remaining estimates indicate that the same counselors increase college readiness, selectivity, and educational attainment.

All together, these results indicate that counselor effectiveness is not unidimensional and good counselors are typically not good at everything. Some counselors appear to specialize in the outcomes they improve, and specialization is most common for the rarer outcomes. Other counselors tend to be pretty good across the board at improving the most frequent outcomes. The main types of outcomes over which counselors appear to specialize are improving non-cognitive skills, increasing educational attainment, and increasing the selectivity of the college a student attends.

7 Predictors of Counselor Effectiveness

In this section, I use the quasi-random assignment of counselors to measure how being assigned to a counselor with a particular characteristic, experience, or level of education causes student outcomes to change. I control for the first letter of the student's last name, cohort, school and assignment grade fixed effects, the gender and race of the student and counselor, as well as the student's academic achievement and demographics (X_{ij}).[36]

$$Y_i = \alpha_0 + \alpha_1 CounselorType_j + \beta X_{ij} + \nu_n + \delta_s + \gamma_g + \psi_t + \epsilon_{iy} \tag{12}$$

The estimate, α_1, indicates how being assigned to a counselor of a certain type is causally linked to a student's outcome. These estimates may not indicate the true causal effect of a counselor's education or demographics on the student, since these characteristics may be correlated with a counselor's unobservable experiences or attributes. Nevertheless, these predictors can be useful for school administrators deciding who to hire or how to match students to counselors.

7.1 Demographics

Table 8 indicates that students assigned to a counselor of the same racial group are about two percentage points more likely to graduate high school, attend college and persist than their peers who were assigned to a counselor from a different race.[37] These effects are largest for non-white students, who are 3.8 percentage points more likely to graduate high school and attend college if matched to a non-white counselor.

Minority students may benefit from being matched to a minority counselor if these counselors

[36] The student level control variables are the same as those used in the effectiveness estimates.

[37] To deal with small racial groups I focus on whether students were assigned to a white counselor or a non-white counselor. There are too few Hispanic and Asian counselors to use narrower racial groupings.

have a better understanding of students' experiences and needs. For instance, minority counselors may know more about the unique hurdles faced by minority students in college access and the types of colleges which are likely to be the best fit. Research on teachers also indicates that minority educators may serve as role models (Dee, 2005; Gershenson et al, 2019). Unlike the teacher setting, however, I find that white students also benefit from same-race matches, and white students typically have many potential role models in schools.

These effects could also be explained by how much students trust their counselor. There is often considerable discretion on both the student and counselor side in how they interact with one another. Students may be more willing to reach out to counselors if they share some observable characteristic. The same may be true for counselors. In addition, counselor discrimination could explain these effects if counselors provide less support for students who look different from them.

There is no detectable benefit from matching students to counselors based on their gender (Figure 6). If anything, there may be a negative effect, particularly for males (Table A.14).

7.2 Education

Next, I show that the undergraduate college a counselor attended is predictive of whether and where her students attend college. Data on counselors' undergraduate and graduate education are available for about 20% of the counselors in my sample.[38] Master's degrees are required for all counselors in Massachusetts and since very few counselors have doctorates, I focus on the type of colleges at which counselors received their undergraduate and master's degrees.

Table 8 shows that the location of the counselor's undergraduate college is a strong indicator of counselor effectiveness. Students assigned to counselors who received their bachelor's degree in Massachusetts are 2.5 percentage points more likely to graduate high school than those assigned to a counselor who earned one outside of the state. There are similar effects for college attendance and the graduation rate of the college attended. 59% of students in the education sample have a counselor who earned a bachelor's degree in Massachusetts. These counselors may have a better

[38]Education data are self-reported by the counselors. They are not required to report it on the forms from which the data are drawn. Table 2 compares these counselors to others in terms of experience and demographics. On average, they look similar to the full sample.

understanding of the local college options, the needs of local students, or state graduation requirements than counselors educated elsewhere.[39] Receiving a master's degree in Massachusetts is not associated with higher student educational attainment, possibly because the location of master's institutions are less predictive of where one attended high school than undergraduate institutions. This is consistent with the hypothesis that local knowledge of the education system is beneficial.[40]

I find no evidence that counselors who attended more selective undergraduate or master's institutions are more effective than their peers, but these estimates are quite noisy. Table A.15, however, provides some evidence that counselors guide students to attend colleges which are similar to where they attended. Students with a counselor who attended an elite college are about 2 percentage points more likely to attend an elite college. Counselors who attended a public college also shift attendance to public colleges, and those who attended large undergraduate institutions increase student attendance at large institutions and highly selective colleges. Thus, counselors may use their own college experiences to guide the recommendations they provide to students.

7.3 Experience

Most measures of counselor experience are not positively related to student outcomes. Counselors with teaching licenses reduce high school graduation and supervisors have lower rates of four-year college enrollment than other counselors (Table A.14). The point estimates for other outcomes are also negative but not statistically significant. This indicates that school administrators should probably not consider teaching experience a bonus when hiring counselors. These results may be driven by differential skill requirements for teachers and counselors, or counseling may be a path selected by the least effective teachers when they leave the profession. The negative effects for supervisors may be because they have less time to serve students. It could also be related to who is selected to be a supervisor. Supervisors typically have smaller caseloads, so less effective counselors may be selected, or select into, the role. I find no evidence that effectiveness is predictive of who becomes a supervisor (Table A.16).

[39]This relationship could be driven by the fact that counselors educated in Massachusetts are also more likely to have attended high school in Massachusetts.

[40]In addition, more students have a counselor with a Master's degree from a Massachusetts institution than an undergraduate degree (77% vs. 59%), so this criteria differentiates counselors less.

Next, I show that years of experience are not positively related to student outcomes. I follow Papay and Kraft's (2015) approach to control for year and counselor effects. I estimate the year fixed effects in a first stage regression and then use the estimated effects ($\hat{\delta}_y$) in a second stage regression with counselor fixed effects (μ_j), name fixed effects (ν_n) and student level controls (X_i). This enables the inclusion of counselor and year effects while addressing the collinearity of experience and years. I also use the log of experience since the returns to experience are often non-linear.

Table 8 indicates that novice counselors perform marginally better than more experienced counselors, but these estimates are quite noisy. Students assigned to a novice 9th grade counselor are 1 percentage point more likely to graduate high school. Students also benefit from being assigned to a novice 11th or 12th grade counselor. Panel (C) of Table 8 indicates that the returns to experience are negative, but Figure A.2 shows that these estimates are quite noisy. Counselors with more experience may not be more effective than newer counselors if there are benefits to being close in age to students or if counseling skills rapidly depreciate. For instance, newer counselors may be more likely to have received training on the state's current counseling standards. They may also be more familiar with technological innovations in the college application process or with other aspects of teen culture that make it easier for them to relate to students.

8 Comparing Counselor Effectiveness to Other Education Inputs

The evidence presented in the previous sections indicates that the counselor to which a high school student is assigned has a significant impact on educational attainment. From a policy perspective, it is important to understand how important counselor effectiveness is relative to other education resources given limited resources for improving student outcomes. In this section, I show that hiring an additional counselor in every Massachusetts high school is unlikely to lead to larger benefits than increasing counselor effectiveness by one standard deviation. I also show that counselor effects are similar in magnitude to the best estimates of teacher effects on high school graduation and college attendance. Finally, I describe the similarity between counselor effects and those of previously studied college-going interventions.

8.1 Caseloads

School counselors typically serve many students, with the average high school counselor serving about 250 students. This is lower than the K-12 average of 455, but many high schools are still well above the 250 student caseload recommended by the National School Counselor's Association. Given the potentially time intensive nature of advising, one may expect caseload sizes to have large effects on how effectively counselors can serve students. If, however, counselors have found ways to efficiently serve many students, such as with group sessions or using technology to provide individualized guidance at scale, caseloads may not have large impacts on student success.

Counselor caseloads are difficult to study because they are endogenous. Schools in high income areas with high achieving students and lots of resources typically have the smallest caseloads. Panel (A) of Figure 7 shows that four-year college enrollment rates are highest at schools with smaller caseloads, but this relationship is insignificant and nearly flat when, in Panel (B), I control for student achievement and demographics (or in Table 9 when I add school and year fixed effects). Thus, the true relationship between caseload and student outcomes may be quite small.

To address the endogeneity in caseloads, I use five approaches to measure the relationship between caseloads and educational attainment in Massachusetts high schools.[41] I focus on the impact of 9th grade caseloads on high school graduation since many dropouts leave in early grades. For the college outcomes, I focus on 11th grade caseloads since students make many decisions in 11th grade which affect college attendance.[42]

First, I control for student characteristics and school fixed effects. Panels (B) and (C) of Table 9 indicate that controlling for student characteristics or school and year fixed effects eliminates the significant OLS relationship between caseloads and most measures of educational attainment.

Second, I use within school variation in the size of the student body over time as an instrument

[41] For these analyses I use the full population of Massachusetts high schools and students. I compute average caseloads in a school and year based on the number of full-time-equivalent counselors and students in a school. Using all schools, instead of just those in the quasi-random assignment sample, increases my power a lot. I also use average caseloads instead of the number of students linked to a counselor because more effective counselors may be assigned more students. My results are similar but noisier if I limit my sample to schools for which I observe linkages or if I use caseloads based on student-counselor linkages.

[42] Estimates for 12th grade caseloads and college attendance are similar but slightly smaller.

for caseload size (similar to Bound & Turner, 2007). I include school and year fixed effects as well as school-specific time trends, controls for the number of counselors at the school, and the size of the student's cohort. Table 9 indicates that a 100 student increase in caseloads, based on this variation, is associated with a 1.1 percentage point decrease in high school graduation and a marginally significant 1 percentage point decrease in four-year college attendance.

Third, I restrict this instrument to use variation in the number of students outside of a student's own cohort to control for how cohort size affects access to other school resources. Panel (C) of Figure 7 shows that four-year college attendance is also lower when caseloads are larger due to within school variation in the number of students in other grades. The slightly larger estimates for a 100 student increase in the caseload of other grades (rather than the school) is mostly because this change is equal to about a 133 student increase in average caseloads.

On average, hiring a new counselor in a Massachusetts high school would reduce full caseloads by 74 students and caseloads in other grades by 46 students. Thus, the estimates from panels (E) and (F) of Table 9 suggest that, on average, hiring a new counselor would increase high school graduation and four-year college attendance by .6 to .8 percentage points. The last row of Table 9 indicates that the benefits may be twice as large for low achieving students.

Fourth, I use within school variation in the number of counselors over time. Estimates based on this approach indicate potentially smaller benefits to hiring additional counselors. Panel (D) of Figure 7 shows a nearly flat relationship between caseloads and four-year college attendance when caseloads vary due to the number of counselors in a school. Panel (D) of Table 9 indicates that the only significant relationship associated with changes in the number of counselors is in college graduation rates.

Finally, I do an event study around when schools hire or lose counselors. Event study plots (Figure A.3) show that adding an additional counselor leads to a small (and very noisy) increase in high school graduation for 9th-11th graders and four-year college attendance for 11th and 12th graders. These estimates are quite noisy, but the 95% confidence intervals indicate that we can reasonably rule out increases in high school graduation and college attendance that are larger than 3 percentage points when a new counselor is added. Similarly, the reduction in graduation rates when a counselor leaves is less than 3 percentage points.

Together, these results suggest that caseloads are probably negatively related to educational attainment, but I can rule out large returns to hiring additional counselors in most Massachusetts high schools. Massachusetts caseloads are close to the national average for high schools. However, there may be larger returns to reducing caseloads in places with much larger caseloads or in places with many low achieving students. I find much larger benefits for these students. In addition, my estimates only use limited variation in caseloads. It is possible that much larger swings in caseloads lead to much larger changes in student outcomes.[43] Caseloads may also matter for outcomes, such as mental health, which I cannot measure with my data. Finally, changes in technology over time may be making caseloads less important. Counselors can now email many students simultaneously, and education resources, such as Naviance, enable counselors to quickly reach many students, track their progress, and provide personalized recommendations at scale.

My largest point estimates suggest that hiring an additional counselor in the average Massachusetts high school will increase high school graduation and four-year college attendance by about half as much as increasing counselor effectiveness by one standard deviation. These estimates, however, are likely to be biased upwards because they are based on variation in high school size, which impacts access to other school resources. My other estimates indicate that the benefits of caseloads may be smaller. In addition, hiring additional counselors is expensive, and hiring more, but ineffective counselors, could hurt educational attainment more than leaving caseloads at their current level.

8.2 Teacher Effects

My estimates of counselor effects are similar to the best estimates of teacher effects on educational attainment. Chetty, Friedman & Rockoff (2014) find that a one standard deviation better 3rd to 8th grade teacher, as measured by test scores, increases college attendance by .8 percentage points. This is about half as large as the increase expected in college enrollment from assignment to a one standard deviation better high school counselor. Test score value-added may, however, understate

[43] The standard deviation of within school variation in other grade caseload sizes is 27 students.

teachers' true effects on post-secondary outcomes because they can impact college attendance through channels other than test scores. Teachers in high school may also have larger effects on postsecondary education than elementary school teachers.

To address these concerns, I compare my estimates to those from Jackson (2018). Jackson's estimates are based on 9th grade teachers and they incorporate teacher effects on long-run outcomes through non-cognitive channels, in addition to the test score channel.[44] Jackson's largest estimates suggest that a one standard deviation better teacher increases high school graduation by 1.5 percentage points and four-year college intentions by 1.1 percentage points These estimates are slightly smaller than my estimates for high school graduation and actual four-year college attendance.

Thus, the magnitude of counselor effects are in the same general range as teachers' effects. Whether or not one type of educator is more important than the other is not important. Rather, this comparison illuminates the fact that teachers are not the only important educators and counselors can have long-term effects that are similar to teachers. Given the significant attention and resources devoted to teachers and improving teaching, additional attention may be warranted for counselors. Furthermore, improving the effectiveness of one counselor can impact many more students than improving the effectiveness of one teacher because counselors serve many students.

8.3 College-going Interventions

Finally, I compare the impacts of effective counselors to the effects of recent college-going interventions. A wide array of interventions have been created to help remove barriers to college access and improve the selectivity of the institutions that students attend. These interventions span from simple text message reminders or mailers, to intensive after-school support from professionals.

In general, the most promising results have been from interventions that include personalized assistance (Bettinger et al, 2012; Carrell & Sacerdote, 2017; Castleman & Goodman, 2018). These interventions have larger effects on the samples studied than effective counselors do on the average student, but this is partly because interventions tend to focus on the students who are most

[44]They are also based on some of the same students as the Wake County, NC counselor estimates in section 9.

in need of or most likely to benefit from assistance. Focusing on low achieving students, I find that the best counselor effects on college attendance are similar in magnitude to FAFSA assistance from H&R Block and after school mentoring in New Hampshire (Bettinger et al, 2012; Carrell & Sacerdote, 2017). Thus, my results support prior research showing that personalized assistance can have a large impact on whether and where a student attends college.

One potential benefit of school counselors over student interventions is that counselors already work in nearly every U.S. high school and in many schools around the world. Thus, improving their effectiveness may be a more attainable goal than increasing student access to highly personalized (and often expensive) interventions. While simple information interventions are less expensive, they may not be scalable or able to widely affect students. Recent work suggests that it may be difficult to impact students on a large scale with simple information or even with virtual advising (Bird et al, 2019; Gurantz et al, 2019a; Gurantz et al, 2019b; Sullivan, Castleman & Bettinger, 2019). I also find that assignment to an effective counselor has a larger effect on college attendance and persistence than some effective low-cost nudges (Bird et al, 2019; Castleman & Page, 2015). Counselors may, however, be a useful medium for helping students to gain access to and understand the information disseminated via these campaigns. Research on Naviance shows that counselors influence how students use and respond to college admissions guidance (Mulhern, 2019). Thus, combining scalable guidance with the personalized assistance provided by school counselors may be a way to effectively reach many students.

9 External Validity and Principal Evaluations

In this section, I present results from Wake County, North Carolina to strengthen the external validity of my Massachusetts estimates. Wake County is a more diverse district than Massachusetts and all traditional high schools assign counselors based on student last names. I find similar results in this location, though they are noisier because the sample is about 30% smaller. In addition, Wake County provided data on principals' evaluations of counselors. These data indicate that principal evaluations are not predictive of my measures of counselor effectiveness.

Table A.17 shows the variance in student outcomes due to counselors. In Wake County, the standard deviation of counselor effects on high school graduation is 1.5 percentage points and it is 1.6 percentage points for college enrollment. These estimates are similar to those from Massachusetts. Table A.18 also contains leave-year-out estimates. These estimates are noisier than those from Massachusetts and are smaller in magnitude.[45] The 95% confidence intervals of the predicted effects, for all but one of the leave-year-out measures, also contain one.

Counselor evaluation data are available from 2015 to 2018. I focus on counselors who were evaluated in at least two years during this time period because the reliability of the evaluation scores is much higher with two years of data than one. Principals in North Carolina evaluate counselors on a scale of 0 to 4 and three is the most common score.

Figure A.4 shows that counselors' evaluation scores are not predictive of student outcomes. Scatterplots in Figure A.5 also indicate little correlation between a counselor's average evaluation score and her effectiveness for high school graduation and four-year college attendance.[46] The correlation coefficients in Table A.19 are all less than .2 in absolute value and many are negative.[47]

These correlations indicate that evaluations pick up on a different set of skills and counselor goals than the effects I measure. The items on the evaluation rubric are most focused on how counselors are supporting students within the school, promoting diversity, demonstrating leadership, and implementing an effective counseling program. While there is no clear mention of any of the outcomes for which I have constructed value-added scores, I expected the sections on supporting student success to lead to a total evaluation score which is more highly (and positively) correlated with educational attainment. Overall, this analysis indicates that current evaluation tools are unlikely to identify effective counselors in terms of educational attainment. This is consistent with research on teachers and principal evaluations (Jacob & Lefgren, 2008). New tools may be needed if schools wish to target professional development to counselors who most need guidance on increasing educational attainment.

[45] I use the education index instead of the composite index used in the Massachusetts data because Wake County is missing data on key components of the composite index for many years.

[46] I focus on quantiles because there is little variation in the rounded evaluation scores.

[47] Disattenuating them to account for measurement error only increases them slightly.

10 Conclusion

This paper shows that the counselor to which a high school student is assigned has a large impact on human capital accumulation and educational attainment. This indicates that counselors are an important element of the education production function and that they vary significantly in their effectiveness. Unlike teachers, however, counselors' impacts on educational attainment are not driven by their short-term impacts on student ability. Rather, their effects are largely driven by the guidance they provide students about their education options, and the steps needed to reach them, along with the barriers to educational attainment that they raise or reduce. Together, these results suggest that improving access to the type of guidance provided by the best counselors may be an effective means for increasing educational attainment.

Assignment to a one standard deviation better counselor has a similar impact on high school completion and college enrollment as does assignment to a one standard deviation better teacher. The impact of an individual counselor on student outcomes can, however, be much larger than the impacts of individual teachers because they typically serve more students. Thus, from a policy perspective, improving access to effective counselors may be a simpler and more cost effective way to increase educational attainment than improving access to effective teachers. There are also far fewer counselors than teachers so it is probably cheaper, and possibly easier, to roll out training to them. Furthermore, counselors' limited (and often nonexistent) training on college advising means that even minor training may have large effects on postsecondary outcomes.

Improving counselors' capacity is also related to the growing focus on college-going interventions. School counselors are one of the original, and potentially most accessible, resources for students who need assistance with the college enrollment process. I show that effective counselors can have similar effects to many college-going interventions. Expanding access to effective counselors may, however, be more scalable than rolling out new interventions, because counselors already exist in most schools and many students are taught to seek assistance from them.

Improving access to effective counselors may be a better policy option for increasing educational attainment than reducing counselor caseloads if there is a simple way to improve effectiveness. My largest estimates suggest that hiring an additional counselor in each Massachusetts high school will lead to increases in educational attainment which are slightly smaller than increasing the effectiveness of each student's counselor by one standard deviation. Hiring many counselors is also an expensive policy and could decrease the average effectiveness of counselors in the workforce (Jepsen & Rivkin, 2009). However, it may be a much simpler policy than increasing access to effective counselors. Future research could explore how to increase effectiveness.

Finally, one inexpensive way to increase educational attainment could be to improve the matching of students to counselors. Students benefit from being matched to counselors from the same racial group. Some counselors also specialize in the outcomes they are best at improving. Students may benefit from being assigned to counselors who are best at improving the outcomes most relevant for them. There may, however, be negative consequences from specialization with large caseloads if some types of students require more attention than others. In addition, having many students who need attention at the same time may have adverse consequences. Future research could explore these general equilibrium questions.

In conclusion, this paper shows that high school counselors are an important resource for addressing educational inequities and increasing educational attainment. Future efforts to improve student behavior, high school completion, and college enrollment may benefit from leveraging the positions of school counselors and increasing their effectiveness. Efforts to improve school counseling, or student access to the type of guidance provided by the most effective counselors, may also have important social and economic benefits. Finally, counselors serve in many settings outside of schools. More broadly, these results suggest that counselors have significant potential to sway the choices and outcomes of the individuals they serve.

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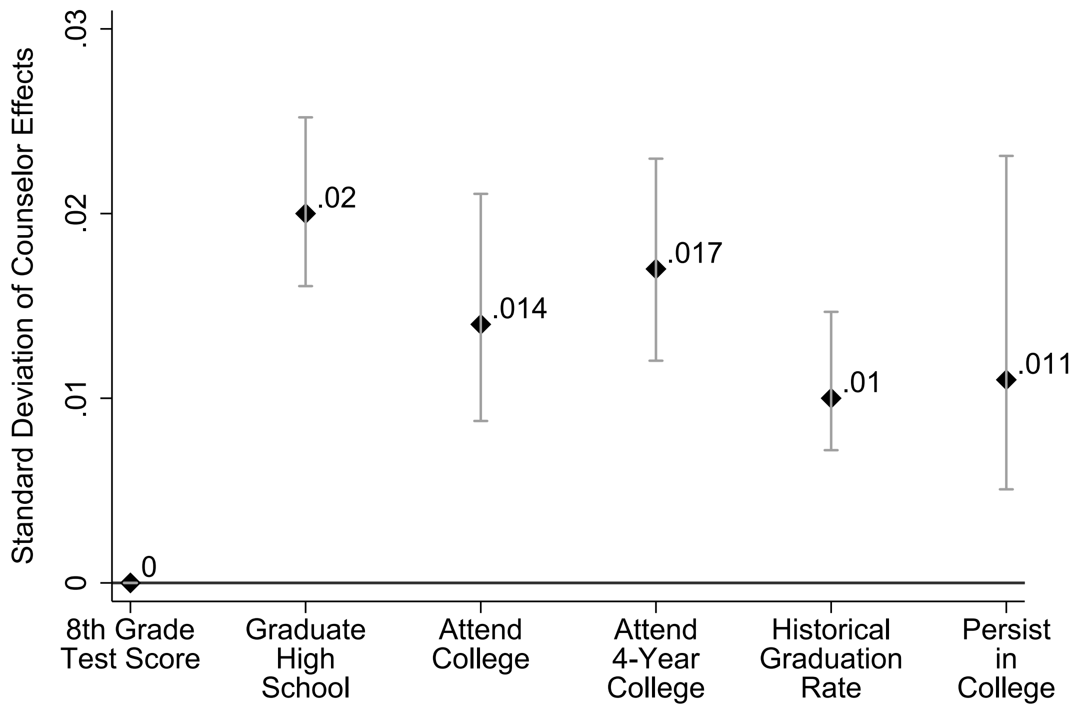
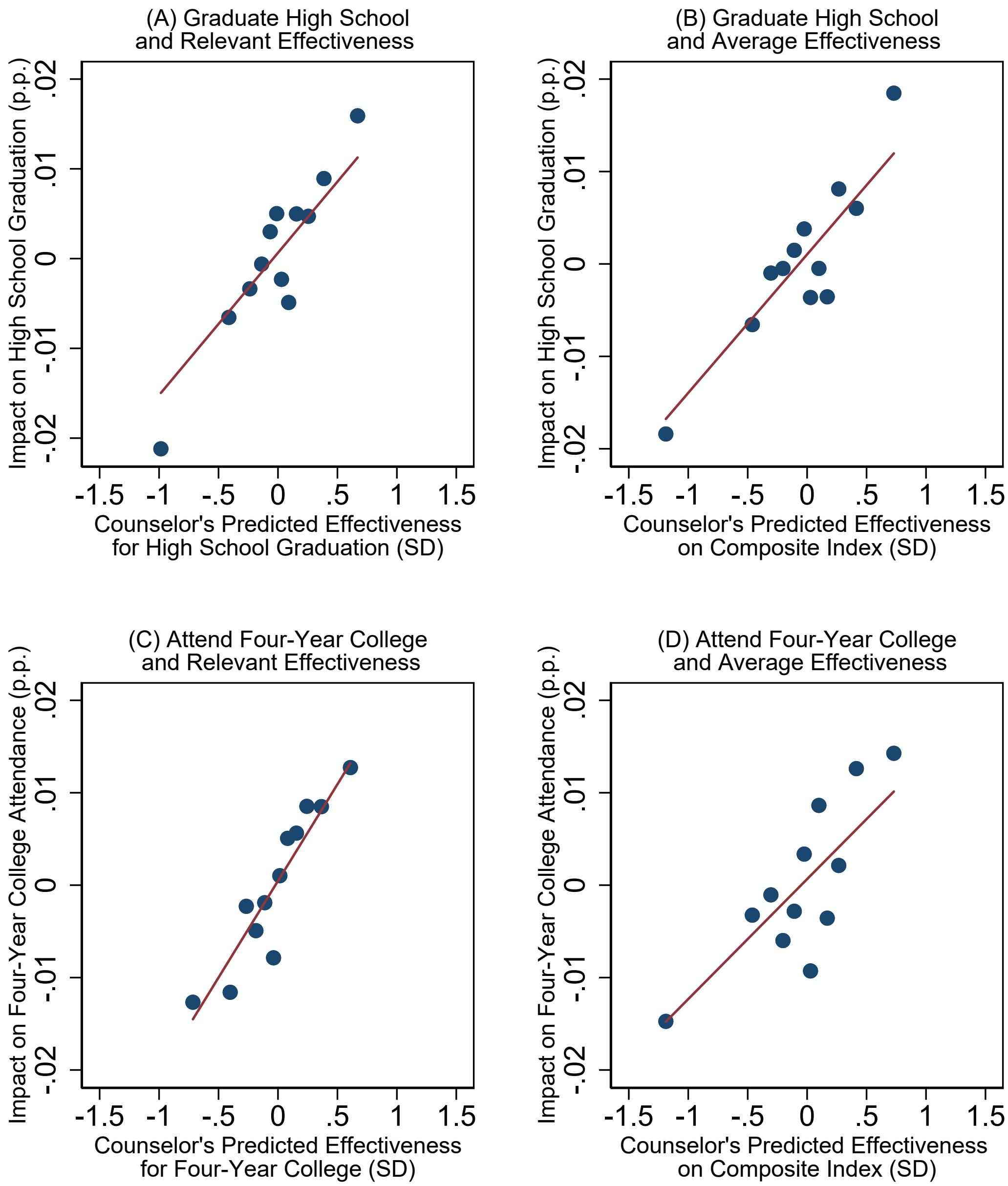
12 Figures and Tables

Figure 1: Standard Deviations of Counselor Effects



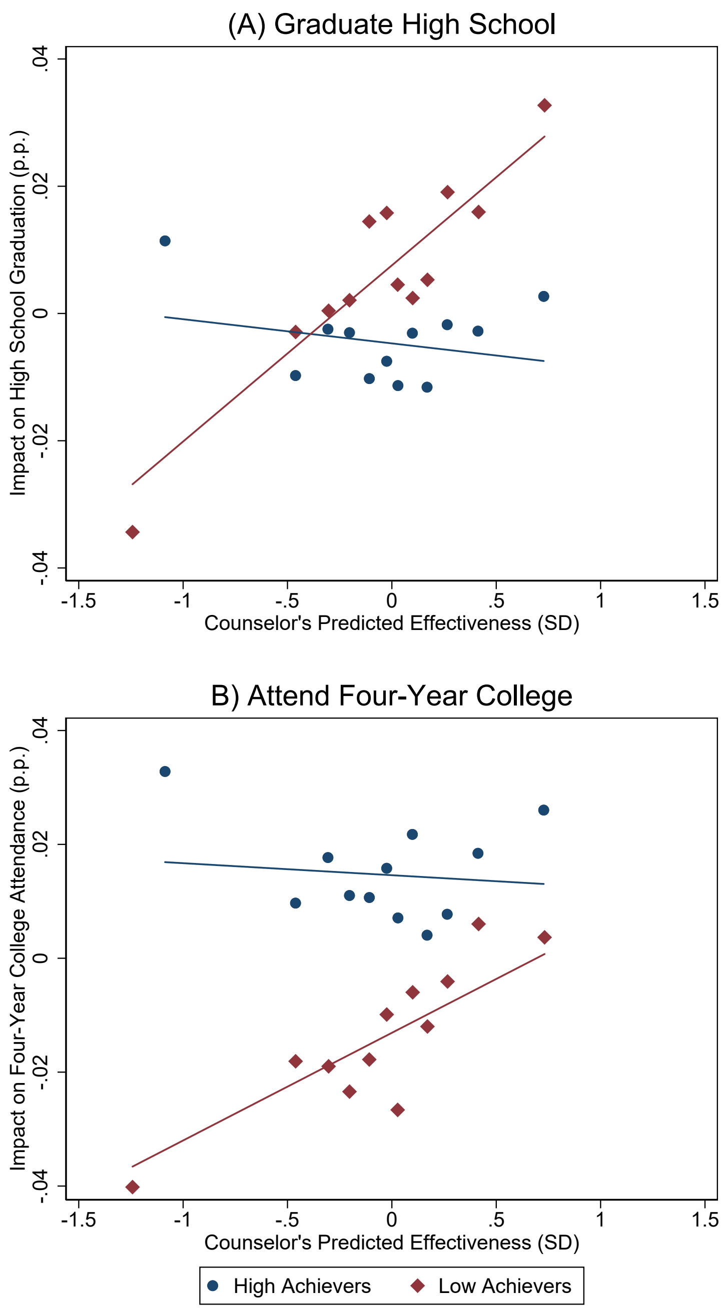
Notes: The figure above indicates the standard deviations of counselor effects. The 95% confidence intervals of the standard deviations are represented by the error bars. The first data point indicates that counselors do not explain any significant variation in students' eighth grade test scores. The remaining estimates indicate that counselors explain significant variation in educational attainment. The test scores are in standard deviation units and the remaining estimates are in percentage points. The standard deviations of counselor effects, and their standard errors, are estimated via restricted maximum likelihood. They condition on the services students received in eighth grade, demographics, eighth grade attendance, eighth grade test scores, high school, cohort, grade of assignment, and first letter of last name. They are based on the first counselor to which students are assigned based on their last name. The standard deviation of counselor effects on eighth grade test scores does not condition on eighth grade test scores but does control for whether students took the eighth grade test. Graduate high school refers to graduating any public high school in Massachusetts. College enrollment is based on enrollment within six months of graduating high school. Historical graduation rate refers to the six-year graduation rate of the college a student attends. It is imputed as zero for students who do not attend college. Similarly, students who do not attend college cannot persist in college. Persistence is defined as returning for a second year of college.

Figure 2: Impacts by Counselors' Predicted Effectiveness



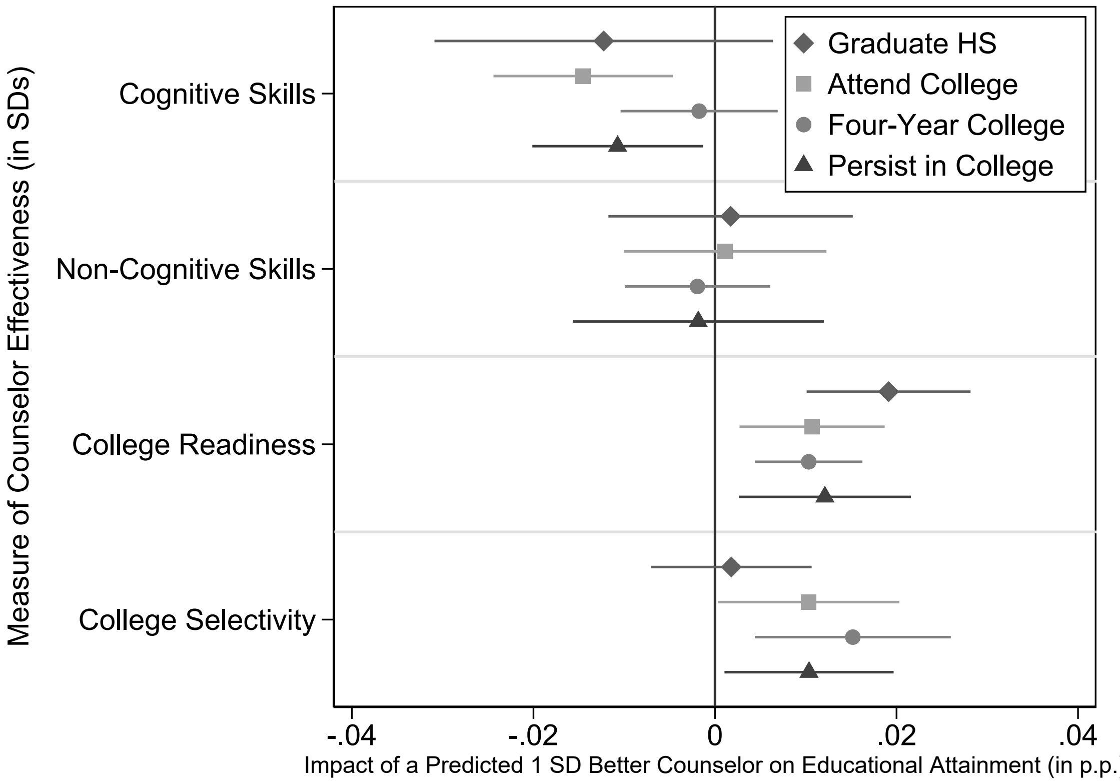
Notes: The figures above are based on binscatters of students' high school graduation (in A and B) or four-year college attendance (in C and D) and their counselors' predicted effectiveness. In panels (A) and (C) counselor effectiveness in terms of the relevant outcome (high school graduation or four-year college attendance) is on the x-axis. In panels (B) and (D) counselors' average effectiveness, in terms of the composite index, is on the x-axis. Counselors' predicted effectiveness is based on the leave-year-out empirical Bayes estimates. The empirical Bayes estimates have been standardized using the estimates in Table 3 and are reported in standard deviation units. The lines are from a regression of student outcomes (high school graduation or college attendance) on their counselors' predicted effects. The slopes of the lines indicate the effects, in percentage points, of assignment to a counselor who is predicted to be one standard deviation above average. Each dot is based on the same number of students. The composite index of effectiveness incorporates effects on educational attainment, cognitive and non-cognitive skills, college readiness, and college selectivity.

Figure 3: Counselor Effects by Prior Achievement



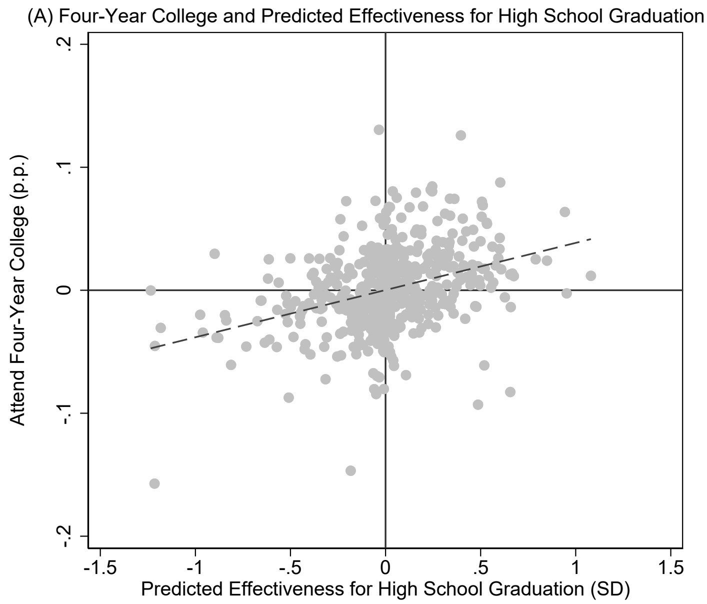
Notes: The figures above are based on binscatters of students' high school graduation (in A) or four-year college attendance (in B) and their counselors' predicted effect on the composite index of effectiveness. Counselors' predicted effects are based on the leave-year-out empirical Bayes estimates. The empirical Bayes estimates have been standardized and are reported in standard deviation units. The lines are from a regression of student outcomes (high school graduation or college attendance) on their counselors' predicted effects. The slopes of the lines indicate the effects, in percentage points, of assignment to a counselor who is predicted to be one standard deviation above average. Each dot is based on the same number of students. Each dot is based on the same number of students. The composite index of effectiveness incorporates effects on educational attainment, cognitive and non-cognitive skills, college readiness and college selectivity. Low-achieving students are those with eighth grade test scores below the state average and high achievers are those with above average eighth grade test scores. High achievers are represented by the navy circles and navy line. Low achievers are represented by the red diamonds and solid red line.

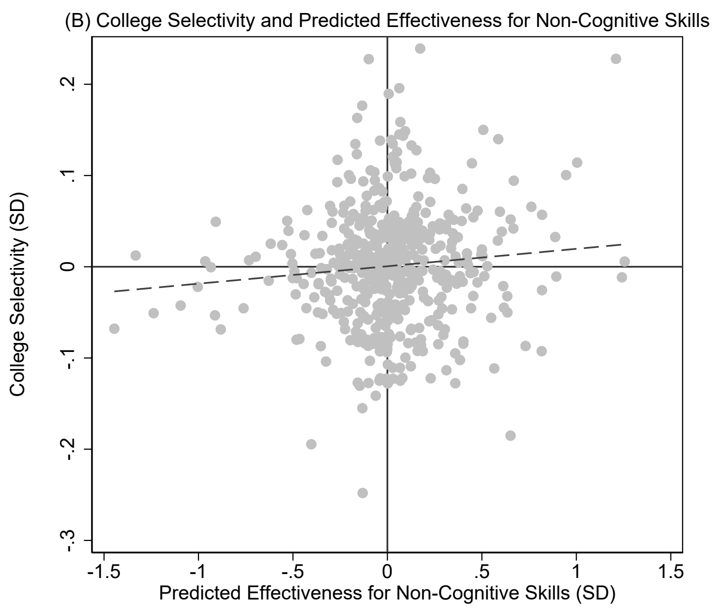
Figure 4: Relationship Between Short-Term Effects and Educational Attainment



Notes: This figure shows the relationship between counselors' predicted effectiveness on four short-term dimensions of effectiveness (cognitive skills, non-cognitive skills, college readiness and college selectivity) and students' educational attainment. The estimates are from regressions of the outcome variable on all four measures of effectiveness in addition to controls for student demographics, eighth grade achievement, eighth grade attendance and services received, as well as school, grade, cohort, and first letter of last name fixed effects. The outcome variables are graduating high school, attending college within six months of the end of high school, attending a four-year college and persisting between a first and second year of college. Persistence is zero for all students who do not attend college. Counselors' predicted effects are based on the leave-year-out empirical Bayes estimates. These estimates have been standardized and are reported in standard deviation units. The point estimates indicate how a one standard deviation predicted better counselor on each dimension increases each measure of educational attainment in percentage points. The bars represent the 95% confidence intervals.

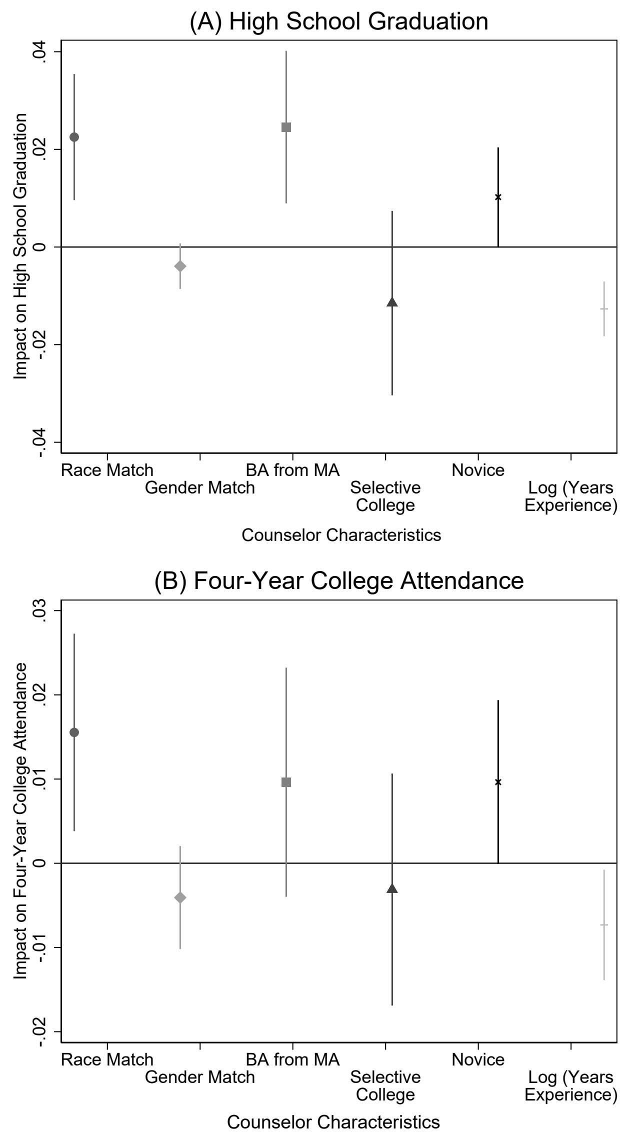
Figure 5: Relationships Between Measures of Effectiveness





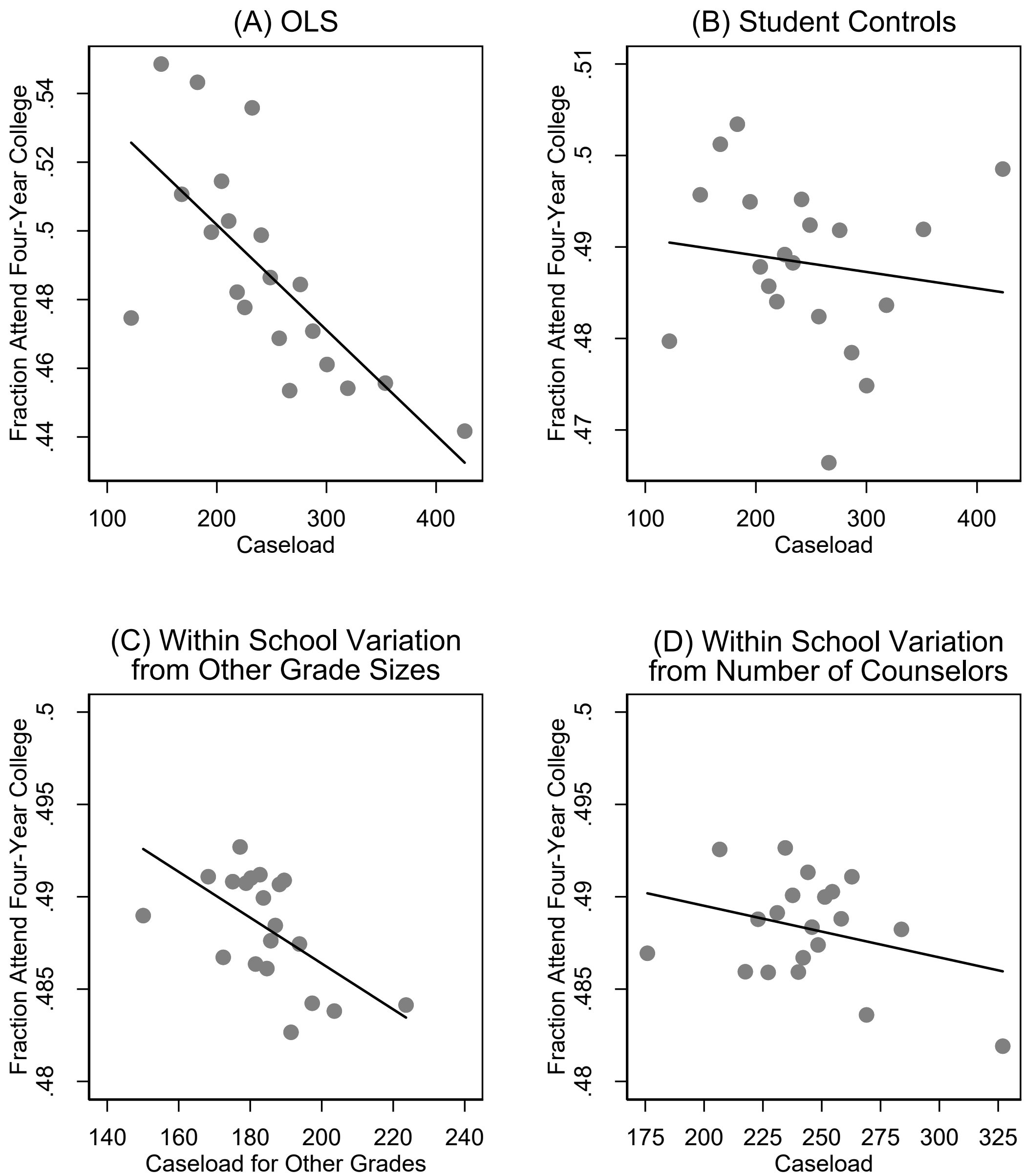
Notes: The figures above show the relationship between counselors' predicted effectiveness in terms of one outcome and their impact on a different outcome. They contain one dot for each counselor. In panel (A), the x-axis represents the counselor's predicted (i.e. leave-year-out) effectiveness in standard deviations for high school graduation. The y-axis indicates the counselor's average impact on four-year college enrollment rates (in percentage points), conditional on student demographics, eighth grade achievement, eighth grade attendance and services received, as well as school, grade, cohort, and first letter of last name fixed effects. The dashed line represents the relationship between counselors' predicted effectiveness in terms of high school graduation and four-year college enrollment rates for the left out students. In panel (B), the x-axis represents the counselor's predicted effectiveness, in standard deviations, for the non-cognitive skills index. The y-axis represents their average effect, in standard deviations, on the college selectivity index. The dashed line represents the relationship between counselors' predicted effectiveness in terms of non-cognitive skills and college selectivity for the left out students.

Figure 6: Counselor Characteristics and Students' Educational Attainment



Notes: The coefficients in figure (A) are from regressions of an indicator for high school graduation on the variable specified on the x-axis. For example, the first estimate indicates the effect on high school graduation of being matched to a counselor who is the same race as the student. Figure (B) shows the impact of the same predictor variables on four-year college attendance. These estimates are all from regressions which include controls for the counselor's and student's race and gender, eighth grade achievement, and characteristics as well as fixed effects for the school and year, and the first letter of the student's last name. The race match estimates are based on matches to white or non-white counselors because of limited diversity in Massachusetts. BA from MA refers to whether the counselor earned a bachelor's degree from a college in Massachusetts. Selective college refers to the whether or not the counselor earned her bachelor's degree from a selective college. (Education data are self-reported by counselors and are only available for 20% of counselors in my sample.) The experience variables on the right are based on a counselor's years of experience as a counselor in Massachusetts when first assigned to a student. Novice is an indicator for being a first time Massachusetts counselor when a student is first assigned to that counselor. Log(Exper) is the natural log of year of experience plus one. The bars represent 95% confidence intervals.

Figure 7: Relationship Between Caseloads and Four-Year College Attendance



Notes: The figures above show binscatters of the relationship between the average number of students per full-time equivalent counselor when a student is in 11th grade and students' four-year college enrollment. Panel (A) is based on a simple OLS regression of college attendance on caseload size. Panel (B) indicates the same relationship but now includes controls for students' eighth grade achievement and demographics. Panel (C) shows the same relationship but only uses within school variation in caseloads due to changes in the number of enrolled students in grades 9, 10, and 12. Panel (D) uses within school variation in caseloads due to changes in the number of full-time-equivalent counselors in the school. The estimates in panels (C) and (D) include controls for the number of students in one's grade, school-specific time trends, and year fixed effects. The estimates in panel (C) also control for the number of counselors in the school, while the estimates in panel (D) control for the number of students in the school.

Table 1: Student Summary Statistics

	All	Match to Counselor: Main Sample	Match to Counselor: In HR Sample	Match to Counselor: Ed Sample	Caseload Sample
	(1)	(2)	(3)	(4)	(5)
(A) Demographics					
White	0.69	0.81	0.80	0.78	0.71
Asian	0.05	0.04	0.04	0.04	0.05
Black	0.10	0.05	0.05	0.06	0.09
Hispanic	0.15	0.09	0.09	0.11	0.14
Limited English	0.17	0.05	0.05	0.08	0.16
Special Ed	0.19	0.17	0.17	0.18	0.18
Free/Reduced Lunch	0.41	0.30	0.31	0.33	0.40
Gr. 8 Test	-0.00	0.18	0.17	0.14	0.04
(B) HS Academics					
Days Truant	7.1	7.3	7.7	10.6	7.6
Suspended	0.19	0.13	0.12	0.12	0.18
Took AP Test	0.28	0.37	0.38	0.38	0.31
GPA	2.65	2.79	2.79	2.76	2.67
Took SAT	0.56	0.67	0.66	0.67	0.60
SAT Score	1498	1531	1524	1492	1504
Graduate High School	0.78	0.87	0.87	0.87	0.82
(C) College Outcomes					
Attend College	0.56	0.67	0.66	0.67	0.60
Four-Year College	0.42	0.54	0.54	0.54	0.45
Highly Selective	0.09	0.12	0.12	0.12	0.09
Persist 1st Year	0.46	0.57	0.57	0.57	0.50
Earn BA	0.30	0.43	0.42	0.42	0.34
(D) Counselor Assignments					
Number of Counselors	0.20	1.13	1.12	1.10	0.24
N	819,268	142,161	141,953	33,326	658,791

Notes: Column 1 contains all students in a MA high school who were projected to graduate between 2008 and 2017. Column 2 contains all students in column 1 who were matched to a counselor with students in at least two different cohorts and who had at least 20 students in their own cohort. This is the sample used for the main effectiveness estimates. Column 3 contains all students matched to a counselor in the Human Resources Database. (It includes some counselors with only one cohort of students and some students in cohorts with less than 20 students. Column 4 contains all students who were matched to counselor with a record in the Human Resources Database who also self-reported their education. Column 5 contains all students in column 1 who were enrolled in a school in a year with a valid measure of full-time equivalent counselors. This means there were at least .5 FTEs in the school and the caseloads were computed to be between 100 and 500 students. I apply this restriction to ensure that the caseload estimates are not biased by outliers due to errors in the data. Limited English is an indicator for whether the student was an English language learner in high school. Special Ed is an indicator for whether the student ever received special education services in a public Massachusetts high school. Free/Reduced lunch is an indicator for whether the student received free or reduced-price lunch in high school. Days truant refers to the number of unexcused absences a student has in high school. GPA data are not available for all years. GPAs are on a four-point scale and are computed based on reported grades in core courses. SATs are on the 2400 scale. Attend college is an indicator for whether the student attended college within six months of graduating high school. Highly selective is an indicator for attending a highly selective college as classified by Barron's rankings in 2009. Persist 1st Year is an indicator for whether a student persists between their first and second years of college. BA is an indicator for earning a Bachelor's degree within five years of starting college. All remaining outcomes represent the fraction of students in the sample achieving that outcome.

Table 2: Counselor Summary Statistics

	All in HR Records	Assignments	HR and Assignments	Ed Data
(A) Demographics				
White	0.87	0.97	0.97	0.80
Black	0.06	0.01	0.01	0.10
Asian	0.02	0.00	0.00	0.02
Hispanic	0.04	0.01	0.01	0.06
Male	0.26	0.27	0.27	0.22
(B) Experience				
Master's	0.84	0.95	0.95	0.83
Doctorate	0.02	0.03	0.03	0.02
Supervisor	0.09	0.12	0.12	0.06
Teacher	0.13	0.08	0.08	0.11
Avg Exper	2.72	4.38	4.38	2.72
Switch in MA	0.27	0.23	0.23	0.30
(C) Counselor Assignments				
Students Matched to Counselor	196	258	263	184
Students Matched per Cohort	44	61	61	42
Students Matched per Year	180	184	186	185
Counselor Years in Sample	3.5	4.5	4.5	3.2
Counselors	3328	510	377	99

Notes: Column 1 contains all counselors in the HR records who worked in a high school. Column 2 contains all counselors in who I match to students. Column 3 contains all counselors who are both in the HR records and matched to students. Column 4 contains all counselors from column 3 who also reported in the HR file where they received their undergraduate degree. The education data are all self-reported. School counselors in Massachusetts are required to have Master's degrees. Teacher indicates whether the counselor has a valid teaching license. Supervisor is an indicator for whether the counselor was ever a counseling supervisor in Massachusetts. Avg Exper refers to the average years of experience of the counselors in Massachusetts as a counselor. Switch in MA indicates the fraction of counselors who switched schools within Massachusetts.

Table 3: Standard Deviations of Counselor Effects

	Standard Deviation (1)	Standard Error of SD (2)	Mean (3)	Percent Change (4)	N Students (5)
(A) Placebo Test					
8th Grade Test	0.000	(0.000)	0.15	0%	142,161
Math Test	0.000	(0.000)	0.15	0%	142,161
Reading Test	0.000	(0.000)	0.15	0%	142,161
(B) Educational Attainment					
Graduate High School	0.020***	(0.002)	0.87	2%	142,161
Attend College	0.014***	(0.003)	0.67	2%	142,161
Attend Four-Year	0.017***	(0.003)	0.54	3%	142,161
Persist 1st Year	0.011***	(0.004)	0.57	2%	121,041
Education Index	0.041***	(0.005)	0.33		142,161
(C) High School Outcomes					
Ever Suspended	0.028***	(0.003)	0.13	22%	142,161
10th Grade Test	0.000	(0.000)	0.17	0%	121,634
HS GPA	0.000	(0.000)	2.79	0%	121,314
Log Absences	0.000	(0.000)	3.34	0%	142,161
Took AP Test	0.015***	(0.005)	0.37	4%	142,161
Took SAT	0.042***	(0.004)	0.67	6%	142,161
Max SAT	50.7***	(6.6)	1531	3%	142,161
(D) College Type					
Selective College	0.015***	(0.003)	0.39	4%	142,161
Historical Grad Rate	0.010***	(0.004)	0.38	3%	142,161
Average Net Price	0.0	(0.0)	13,243	0%	142,161
Mean Student Income	445***	(161)	42,323	1%	142,161
STEM Major	0.008***	(0.003)	0.30	3%	142,161
(E) Indices					
Composite Index	0.052***	(0.006)	0.27		142,161
Cognitive Skills	0.015***	(0.008)	0.18		121,045
Non-cognitive Skills	0.045***	(0.006)	0.11		142,161
College Readiness	0.080***	(0.008)	0.24		142,161
College Selectivity	0.029***	(0.006)	0.23		142,161
Education	0.041***	(0.005)	0.27		142,161

Notes: (*p<.10 **p<.05 *** p<.01). Significance levels are from a likelihood ratio test comparing models with and without counselor effects. The estimates above are the standard deviations of counselors' effects in Massachusetts. They are estimated from a multi-level model with random effects for counselors and counselor by cohort shocks. Standard errors of the standard deviation estimates are in column (2). These are obtained directly from the maximum likelihood estimation. All estimates are from models which include fixed effects for the first letter of the student's last name, school, grade, and year (when a student was first assigned to the counselor), as well as random effect parameters for counselor by cohort shocks. Estimates are based on the first counselor to which a student is quasi-randomly assigned. Estimates also contain controls for the student's 8th grade test scores, English language proficiency, special education receipt, receipt of free or reduced price lunch, receipt of title 1 services, existence of a 504 plan, enrollment in 8th grade in an MA public school, days absent, days truant, indicators for race (Black, white, Asian or Hispanic) and gender. The estimates in panel (A) do not control for 8th grade test scores. All estimates are based on 510 counselors. Estimates in panel (A) and (E) are in standard deviation units (based on the population of Massachusetts students). Estimates in Panel (B) are in percentage points. The impacts in panels (C) and (D) for binary outcomes are in terms of percentage points and the other effects are in the relevant units. Ever suspended refers to whether the student was ever suspended in high school. High school GPAs are out of a maximum of four. The SAT scores are reported on a 2400 point scale. Log Absences refers to the natural log of days absent plus one (to deal with zeros). College selectivity is an indicator for attending a selective college and it is based on the Barron's 2009 rankings. Historical graduation rate refers to the historical six-year graduation rate at the college a student attends. (It is imputed as zero for students who do not attend college). The average net price is the average price paid by in-state students after accounting for grants, as reported to IPEDS in 2015. Mean Student Income refers to the average income of students attending the college as reported by Chetty et al (2017). The indicator for a STEM major is based off the major and degree codes reported to NSC.

Table 4: Validity of Predicted Effects

	Graduate High School (1)	Attend College (2)	Attend Four-Year (3)	Indices (SD) Education Index (4)	Cognitive Skills (5)	Non-Cognitive Skills (6)	College Readiness (7)	College Selectivity (8)	Composite Index (9)
(A) Unit Increase									
Predicted VA	0.946***	1.104**	1.381***	1.178***	1.360*	2.049***	1.358***	1.350***	1.448***
	(0.249)	(0.378)	(0.277)	(0.287)	(0.612)	(0.459)	(0.301)	(0.406)	(0.340)
(B) SD Increase									
Predicted VA	0.019***	0.015**	0.023***	0.048***	0.020	0.093***	0.108***	0.039**	0.075***
	(0.006)	(0.005)	(0.005)	(0.012)	(0.012)	(0.021)	(0.024)	(0.012)	(0.018)
SD of Effects	0.020	0.014	0.017	0.041	0.015	0.045	0.080	0.029	0.052
N	142,161	142,161	142,161	142,161	121,045	142,161	142,161	142,161	142,161

Notes: Heteroskedasticity robust standard errors clustered by counselor and cohort are in parentheses. (*p<.10 **p<.05 *** p<.01). All regressions include fixed effects for the first letter of the student's last name, each school, grade and year (when a student was first assigned to the counselor). Estimates are based on the first counselor to which a student is quasi-randomly assigned. Estimates also contain controls for the student's 8th grade test scores, English language proficiency, special education receipt, receipt of free or reduced price lunch, receipt of Title 1 services, existence of a 504 plan, enrollment in 8th grade in an MA public school, days absent, days truant, indicators for race (Black, white, Asian or Hispanic), and gender. The effects in columns (1) - (3) are in terms of percentage points. Those in columns (4) - (9) are in standard deviation units. The estimates in panel (A) indicate the effect of a one unit better counselor based on the leave-year-out empirical Bayes estimates of counselor effectiveness. The estimates in panel (B) indicate the effect of a one standard deviation better counselor as defined using the standard deviations of counselor effects in Table 3. SD of effects refers to the standard deviation of counselor effects as computed via restricted maximum likelihood in the multi-level model. These are the same as those reported in Table 3.

Table 5: Predicted Counselor Effectiveness (in SDs) and Educational Attainment

	Graduate High School (1)	Attend College (2)	Attend Four-Year College (3)	Historical Graduation Rate (4)	Persist 1st Year (5)	Education Index (6)
(A) Overall Effects						
Composite Index	0.020***	0.015**	0.017***	0.013***	0.014**	0.044***
	(0.005)	(0.005)	(0.004)	(0.003)	(0.005)	(0.010)
(B) Intermediate Indices						
Cognitive Skills	-0.012	-0.015***	-0.002	0.000	-0.011**	-0.024*
	(0.008)	(0.004)	(0.004)	(0.002)	(0.004)	(0.012)
Non-Cognitive Skills	0.002	0.001	-0.002	-0.002	-0.002	0.001
	(0.006)	(0.005)	(0.004)	(0.002)	(0.006)	(0.011)
College Readiness	0.019***	0.011**	0.010***	0.010***	0.012**	0.033***
	(0.004)	(0.004)	(0.003)	(0.002)	(0.004)	(0.008)
College Selectivity	0.002	0.010**	0.015**	0.009*	0.010**	0.023**
	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.009)
(C) Long-Term Effects						
Education Index	0.018**	0.019***	0.021***	0.013***	0.020**	0.048***
	(0.007)	(0.006)	(0.005)	(0.002)	(0.006)	(0.012)
N	142,161	142,161	142,161	142,161	121,041	142,161

Notes: Heteroskedasticity robust standard errors clustered by counselor and cohort are in parentheses. (*p<.10 **p<.05 *** p<.01). All regressions include fixed effects for the first letter of the student's last name, school, grade, and year (when a student was first assigned to the counselor). Estimates are based on the first counselor to which a student is quasi-randomly assigned. Estimates also contain controls for the student's 8th grade test scores, English language proficiency, special education receipt, receipt of free or reduced-price lunch, receipt of Title 1 services, existence of a 504 plan, enrollment in 8th grade in an MA public school, days absent, days truant, indicators for race (Black, white, Asian or Hispanic), and gender. Counselor effectiveness is in standard deviation units and is based on the leave-year-out empirical Bayes estimates of effectiveness. The estimates indicate how much a predicted one standard deviation better counselor increases educational attainment. The effects in columns 1-5 are in percentage points. Those in column 6 are in standard deviation units (of the education index). College attendance is based on attendance within six months of completing high school. Persistence is an indicator for enrolling in a second year of college. Historical graduation rate refers to the six-year graduation rate at the college a student attends. Historical graduation rate and persistence are zero for students who do not attend college within six months of finishing high school.

Table 6: Impact of Predicted Counselor Effectiveness by Student Characteristics

	Graduate High School (1)	Attend College (2)	Attend Four-Year College (3)	Historical Graduation Rate (4)	Persist 1st Year (5)	Education Index (6)
(A) By Prior Achievement						
Low Achievers	0.034***	0.025***	0.025***	0.013***	0.024***	0.069***
	(0.008)	(0.007)	(0.006)	(0.003)	(0.006)	(0.015)
High Achievers	0.000	-0.001	0.003	0.011**	-0.001	0.002
	(0.004)	(0.007)	(0.006)	(0.004)	(0.007)	(0.013)
P-value Diff	0.00	0.02	0.02	0.71	0.01	0.00
Low Achiever Mean	0.79	0.50	0.32	0.20	0.39	-0.13
High Achiever Mean	0.95	0.83	0.76	0.56	0.75	0.65
(B) By Income						
Low Income	0.034***	0.029***	0.022***	0.013***	0.026***	0.071***
	(0.008)	(0.007)	(0.007)	(0.004)	(0.007)	(0.015)
High Income	0.008	0.003	0.012*	0.013***	0.004	0.019
	(0.004)	(0.006)	(0.006)	(0.004)	(0.006)	(0.012)
P-value Diff	0.01	0.01	0.28	0.93	0.05	0.01
Low Income Mean	0.76	0.45	0.27	0.17	0.33	-0.23
High Income Mean	0.92	0.76	0.66	0.47	0.67	0.48
(C) By Race						
Non-white	0.032***	0.022**	0.013*	0.008*	0.018**	0.055**
	(0.010)	(0.009)	(0.007)	(0.004)	(0.007)	(0.018)
White	0.014***	0.012***	0.019***	0.015***	0.012**	0.038***
	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)	(0.008)
P-value Diff	0.07	0.16	0.25	0.15	0.44	0.24
Non-white Mean	0.78	0.54	0.37	0.26	0.42	-0.05
White Mean	0.89	0.69	0.58	0.41	0.60	0.34

Notes: Heteroskedasticity robust standard errors clustered by counselor and cohort are in parentheses. (*p<.10 **p<.05 *** p<.01). All regressions include fixed effects for the first letter of the student's last name, school, grade, and year (when a student was first assigned to the counselor). Estimates are based on the first counselor to which a student is quasi-randomly assigned. Estimates also contain controls for the student's 8th grade test scores, English language proficiency, special education receipt, receipt of free or reduced-price lunch, receipt of Title 1 services, existence of a 504 plan, enrollment in 8th grade in an MA public school, days absent, days truant, indicators for race (Black, white, Asian or Hispanic), and gender. Panel (A) divides students by their 8th grade test scores. Students with scores above the state average are classified as high achievers and those below average are referred to as low achievers students. Panel (B) shows estimates separately by whether the student received free or reduced-price lunch in 8th grade. Low Income refers to students who received free or reduced-price lunch while High Income refers to those who did not. (These are the best measures of income available in the data.) Counselor effectiveness is defined using the composite index of effectiveness and the leave-year-out empirical Bayes estimates of effectiveness. College attendance is based on attendance within six months of completing high school. Persistence is an indicator for enrolling in a second year of college. Historical graduation rate refers to the six-year graduation rate at the college a student attends. Historical graduation rate and persistence are zero for students who do not attend college within six months of finishing high school.

Table 7: Measures of Predicted Effectiveness and Student Outcomes

	Student Outcomes						
				Indices			
	Graduate High School (1)	Attend College (2)	Attend Four-Year College (3)	Cognitive Skills (4)	Non-Cognitive Skills (5)	College Readiness (6)	College Selectivity (7)
(A) Effectiveness for Education							
Graduate High School	0.019***	0.015***	0.012**	0.037	0.048**	0.080***	0.023***
	(0.006)	(0.004)	(0.004)	(0.031)	(0.016)	(0.015)	(0.005)
Attend College	0.015*	0.015**	0.019***	0.016	0.034	0.050***	0.026***
	(0.008)	(0.005)	(0.005)	(0.023)	(0.023)	(0.014)	(0.007)
Attend Four-Year	0.012*	0.018***	0.023***	0.020*	0.020	0.041***	0.037***
	(0.006)	(0.005)	(0.005)	(0.011)	(0.012)	(0.009)	(0.006)
(B) Effectiveness for Indices							
Cognitive Skills	-0.010	-0.012*	0.003	0.018	-0.035	-0.010	0.006
	(0.011)	(0.006)	(0.004)	(0.015)	(0.036)	(0.026)	(0.008)
Non-Cognitive Skills	0.014*	0.009	0.006	0.044	0.093***	0.076***	0.008
	(0.006)	(0.005)	(0.004)	(0.045)	(0.021)	(0.023)	(0.006)
College Readiness	0.020***	0.013**	0.012***	0.049	0.069***	0.108***	0.028***
	(0.005)	(0.004)	(0.004)	(0.039)	(0.015)	(0.024)	(0.007)
College Selectivity	0.013**	0.015**	0.021***	0.017	0.012	0.050***	0.038**
	(0.004)	(0.005)	(0.005)	(0.018)	(0.016)	(0.012)	(0.012)
N	142,161	142,161	142,161	142,161	142,161	142,161	142,161

Notes: Heteroskedasticity robust standard errors clustered by counselor and cohort are in parentheses. (*p<.10 **p<.05 *** p<.01). All regressions include fixed effects for the first letter of the student's last name, school, grade and year (when a student was first assigned to the counselor). Estimates are based on the first counselor to which a student is quasi-randomly assigned. Estimates also contain controls for the student's 8th grade test scores, English language proficiency, special education receipt, receipt of free or reduced price lunch, receipt of title 1 services, existence of a 504 plan, enrollment in 8th grade in an MA public school, days absent, days truant, indicators for race (Black, white, Asian or Hispanic) and gender. These results are based on the leave-year-out empirical Bayes estimates of counselor effects. College attendance is based on attendance within six months of graduating high school.

Table 8: Counselor Characteristics and Student Outcomes

	Graduate High School (1)	Attend College (2)	Attend Four-Year College (3)	Historical Graduation Rate (4)	Persist 1st Year (5)	Composite Index (6)
(A) Race Match						
Race Match	0.023***	0.025***	0.016***	0.005	0.017*	0.040***
	(0.007)	(0.007)	(0.006)	(0.006)	(0.010)	(0.014)
Non-White Match	0.038***	0.038***	0.030***	0.011	0.029	0.079***
	(0.014)	(0.013)	(0.009)	(0.009)	(0.018)	(0.025)
White Match	0.012	0.019*	0.006	0.000	0.010	0.011
	(0.009)	(0.010)	(0.011)	(0.008)	(0.012)	(0.023)
N	142,275	142,275	142,275	142,275	118,307	142,171
(B) Undergrad College						
In Massachusetts	0.025***	0.016**	0.010	0.009**	0.005	0.050***
	(0.008)	(0.008)	(0.007)	(0.004)	(0.010)	(0.017)
Selective	-0.011	0.002	-0.003	0.003	-0.011	-0.020
	(0.010)	(0.007)	(0.007)	(0.005)	(0.009)	(0.019)
N	30,241	30,241	30,241	30,241	24,007	30,232
(C) Years Experience (9th Grade)						
Novice	0.002	-0.003	0.006	0.003	0.004	-0.014
	(0.006)	(0.006)	(0.006)	(0.004)	(0.006)	(0.011)
Log(Years)	-0.012***	-0.008**	-0.006	-0.002	-0.001	-0.028***
	(0.003)	(0.004)	(0.004)	(0.002)	(0.005)	(0.008)
N	87,927	87,927	87,927	87,927	73,612	87,927
(D) Years Experience (12th Grade)						
Novice	0.005	0.004	0.016	0.008	0.011	0.010
	(0.006)	(0.010)	(0.010)	(0.007)	(0.010)	(0.020)
Log(Years)	-0.078***	-0.078***	-0.078***	-0.078***	-0.080***	-0.078***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.014)	(0.012)
N	104,295	104,293	104,293	104,293	85,522	104,281

Notes: Heteroskedasticity robust standard errors clustered by counselor in parentheses. (*p<.10 **p<.05 *** p<.01). All regressions include letter of last name, school, cohort, and grade fixed effects as well as controls for students' and counselors' race and gender. They also include controls for the student's 8th grade test scores, English language proficiency, special education receipt, receipt of free or reduced-price lunch, receipt of Title 1 services, existence of a 504 plan, enrollment in 8th grade in an MA public school, days absent, and days truant. Estimates in panels (A) and (B) are based on the first counselor to which a student is quasi-randomly assigned. Estimates in panel (C) are based on students' 9th grade counselors and those in panel (D) are based on students' 12th grade counselors. Race match is defined as assignment to a non-white counselor for non-white students and a white counselor for white students. Selective college is defined using Barron's 2009 rankings. Novice is an indicator for being in one's first year as a Massachusetts counselor. Log(years) refers to the natural log of one plus the number of years for which a counselor has worked as a counselor in Massachusetts (since the HR data began in 2008). Panels (C) and (D) are based on the counselor's years of experience as of the grade assigned to students (9th or 12th). The effects in columns 1-5 are in percentage points. Those in column 6 are in standard deviation units (of the education index). College attendance is based on attendance within six months of completing high school. Persistence is an indicator for enrolling in a second year of college. Historical graduation rate refers to the six-year graduation rate at the college a student attends. Historical graduation rate and persistence are zero for students who do not attend college within six months of finishing high school.

Table 9: Counselor Caseload Size and Educational Attainment

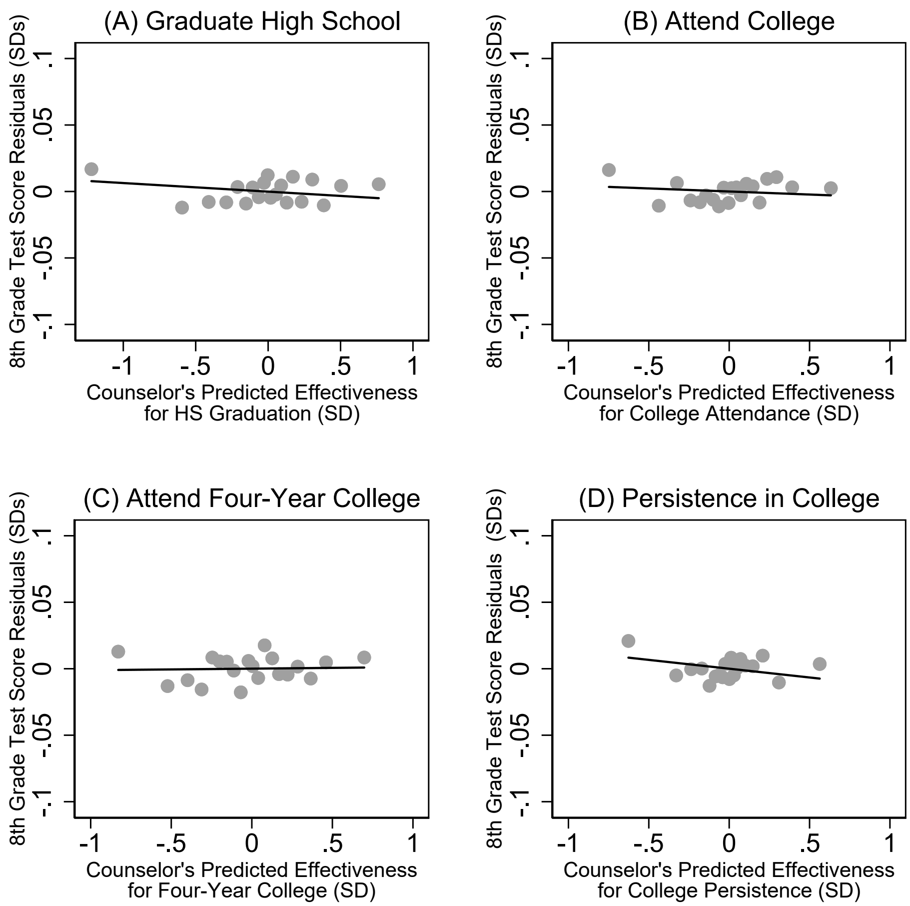
	Grade 9 Caseload	Grade 11 Caseload				
	Graduate High School (1)	Attend College (2)	Attend Four-Year College (3)	Historical Graduation Rate (4)	Persist 1st Year (5)	Composite Index (6)
(A) OLS Caseload						
Caseload (in 100s)	-0.032**	-0.018	-0.031*	-0.039**	-0.020	-0.095**
	(0.012)	(0.011)	(0.015)	(0.013)	(0.012)	(0.035)
(B) Student Controls						
Caseload (in 100s)	-0.008	0.001	-0.004	-0.018**	0.003	-0.034*
	(0.007)	(0.005)	(0.006)	(0.006)	(0.005)	(0.015)
(C) School, Year FE						
Caseload (in 100s)	-0.003	-0.001	-0.000	-0.001	0.000	-0.018**
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.007)
(D) Within School var. from Num. Counselors						
Caseload (in 100s)	0.001	-0.002	-0.003	-0.002	-0.003	-0.006
	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.006)
(E) Within School var. from HS Size						
Caseload (in 100s)	-0.011**	-0.009	-0.010*	-0.008**	-0.003	-0.018
	(0.004)	(0.005)	(0.005)	(0.003)	(0.006)	(0.013)
(F) Within School var. from Other Gr. Size						
Caseload (in 100s)	-0.015**	-0.012*	-0.012*	-0.010**	-0.004	-0.024
	(0.005)	(0.006)	(0.006)	(0.004)	(0.007)	(0.015)
For High Achievers	-0.014*	-0.002	-0.000	-0.011	0.000	-0.019
	(0.007)	(0.007)	(0.009)	(0.006)	(0.009)	(0.020)
For Low Achievers	-0.014*	-0.018**	-0.026**	-0.010	-0.010	-0.027
	(0.007)	(0.008)	(0.008)	(0.006)	(0.008)	(0.018)
N	520,061	594,441	594,441	594,441	530,656	594,441

Notes: Heteroskedasticity robust standard errors clustered by school and year are in parentheses. (*p<.10 **p<.05 *** p<.01). The point estimates represent the change in the outcome associated with a 100 student change in caseloads (or students per counselor). Panel (A) contains estimates based on a simple OLS regression with no controls. The estimates in panel (B) include controls for the student's 8th grade test scores, English language proficiency, special education receipt, receipt of free or reduced-price lunch, receipt of Title 1 services, existence of a 504 plan, enrollment in 8th grade in an MA public school, days absent, days truant, indicators for race (Black, white, Asian or Hispanic), and gender. Estimates in panel (C) includes school and year fixed effects plus school specific time trends (but no student-level controls.) Estimates in panel (D) are from the same specification as those in panel (c) but they also include controls for the size of the school. Thus, the variation in caseloads for these estimates comes from changes in the number of counselors over time within a school. Estimates in panel (E) include school and year fixed effects plus school specific time trends and controls for the number of counselors and students in one's grade. Thus, the variation in caseloads for these estimates comes from changes in the number of students over time within a school. Estimates in panel (F) are from the same specification as those in panel (E), but they use variation in the number of students in other grades served by the average counselor. Panel (F) also contains estimates which are separated by whether students have high (above average) or low (below average) 8th grade test scores. The effects in columns 1-5 are in percentage points. Those in column 6 are in standard deviation units (of the education index). College attendance is based on attendance within six months of completing high school. Persistence is an indicator for enrolling in a second year of college. Historical graduation rate refers to the six-year graduation rate at the college a student attends. Historical graduation rate and persistence are zero for students who do not attend college within six months of finishing high school.

APPENDIX

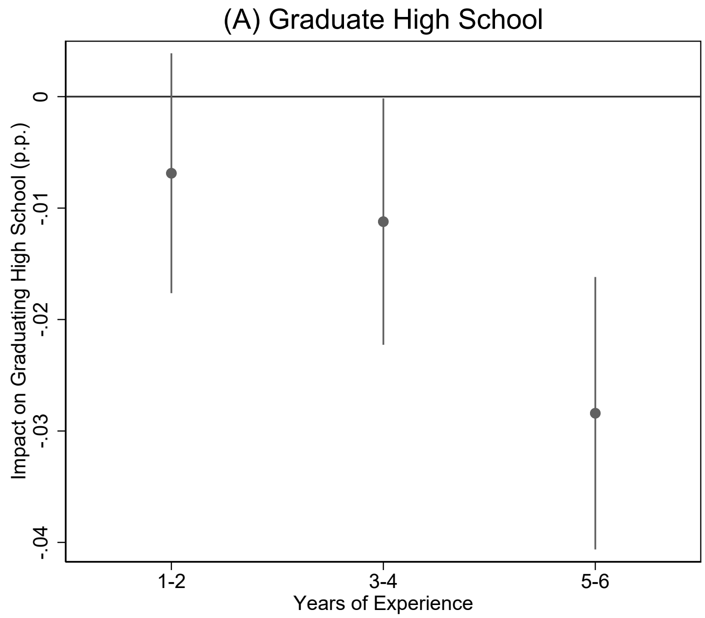
A Additional Figures and Tables

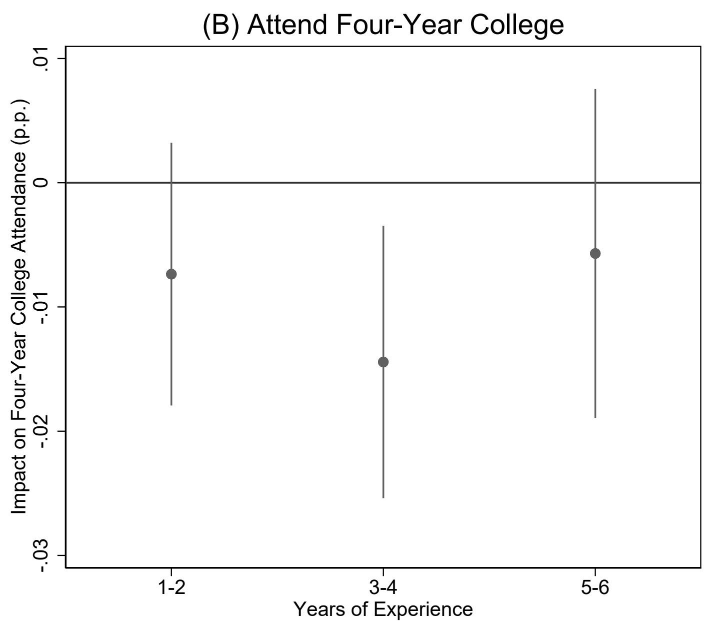
Figure A.1: Placebo Tests



Notes: The figures above show binscatters of counselors' predicted effectiveness and students' eighth grade test scores. The y-axis indicates students' 8th grade test scores (for year *t*) residualized on the first letter of the student's last name, school, grade, and year fixed effects as well as controls for student demographics, services received in eighth grade and eighth grade attendance. The x-axis is based on counselors leave-year-out empirical Bayes estimates of effectiveness. The lines are from regressions of students' eighth grade test scores on their counselors predicted effects. Panel (A) shows counselor effectiveness for high school graduation, panel (B) for college attendance, panel (C) for four-year college attendance and panel (D) for persistence between a first and second year of college. There are the same number of students in each bin. The predicted effects include controls for achievement but the estimates on the x-axis do not. In none of these figures is the relationship between counselor effectiveness and eighth grade achievement significant at the 10% level.

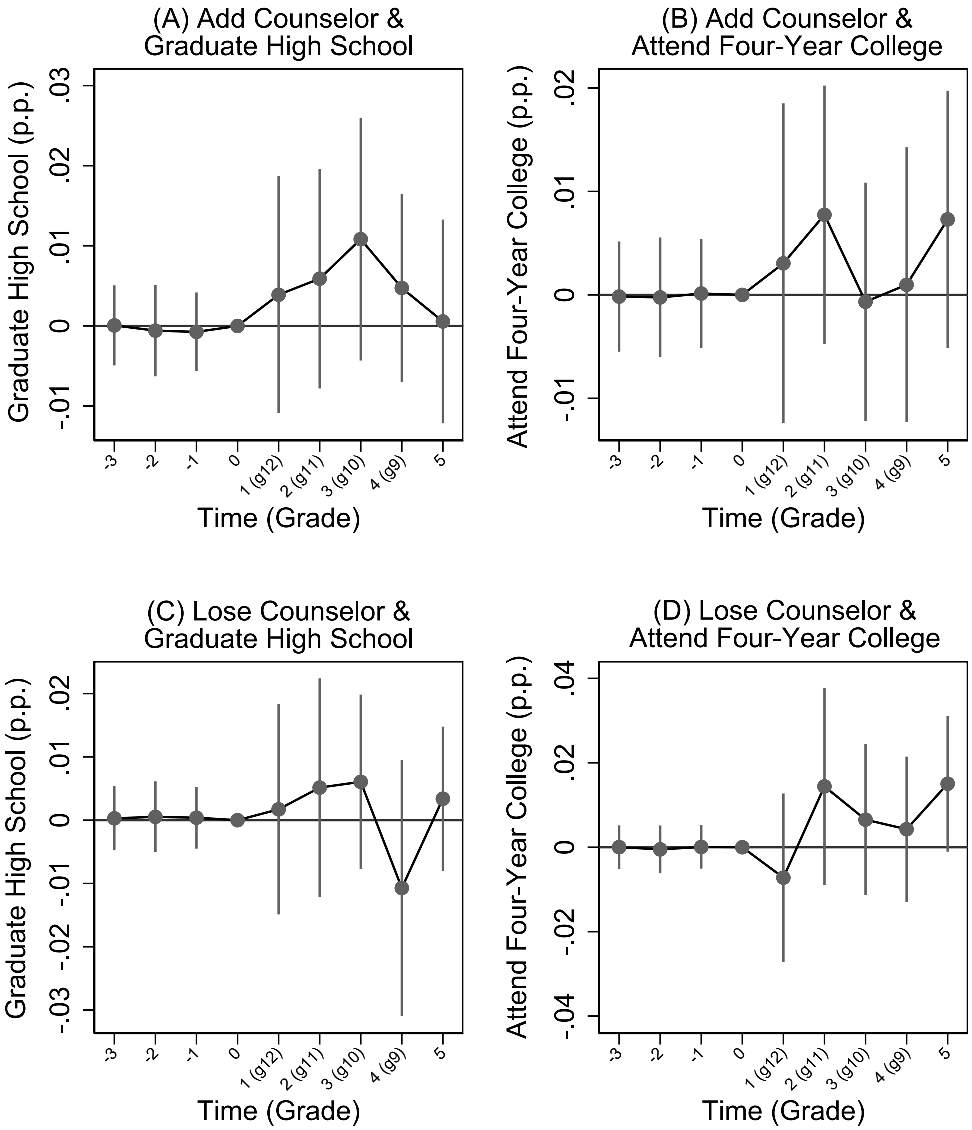
Figure A.2: Impact of Counselor Experience in MA





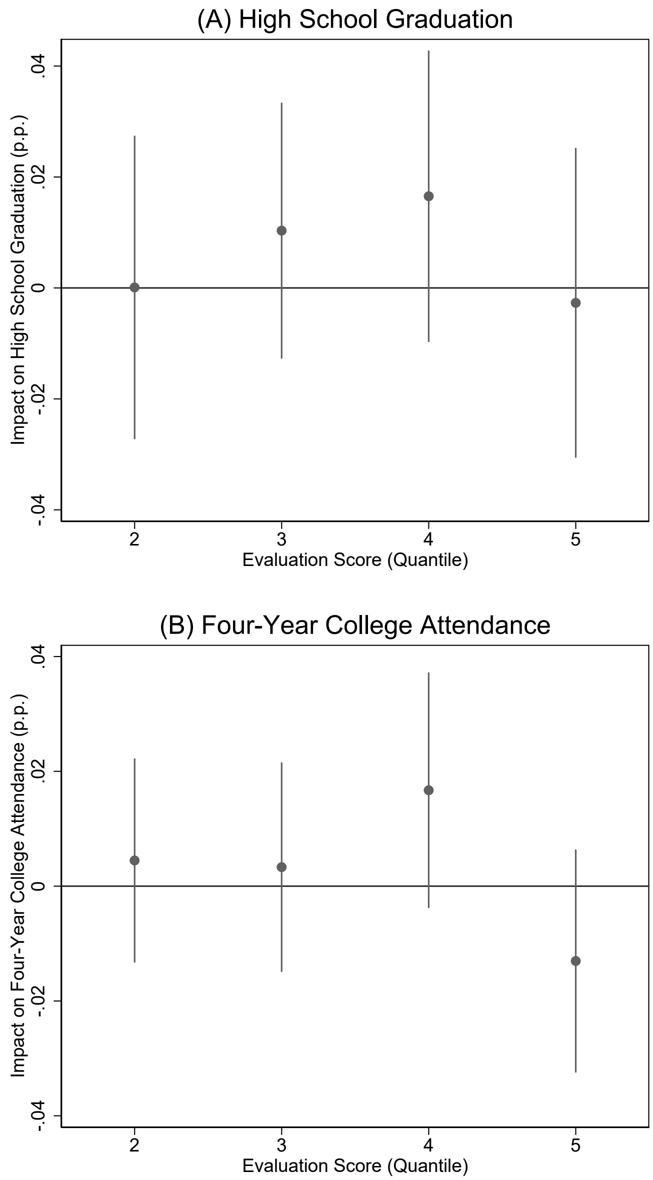
Notes: The figures above show the coefficients from a regression of an indicator for high school graduation (in panel (A)) or four-year college attendance (in panel (B)) on indicators for two-year bins of a counselor's years of experience (in Massachusetts as a counselor). It includes counselor and year fixed effects to account for potential bias in which counselors have a lot of experience. The bars represent 95% confidence intervals. All estimates are relative to novice counselors. Since HR data are only available since 2008, few counselors have more than 6 years of experience at the point when they are first assigned to a student in my sample. These estimates are based on years of experience when first assigned to a 9th grade student.

Figure A.3: Event Study around Number of Counselors in a School



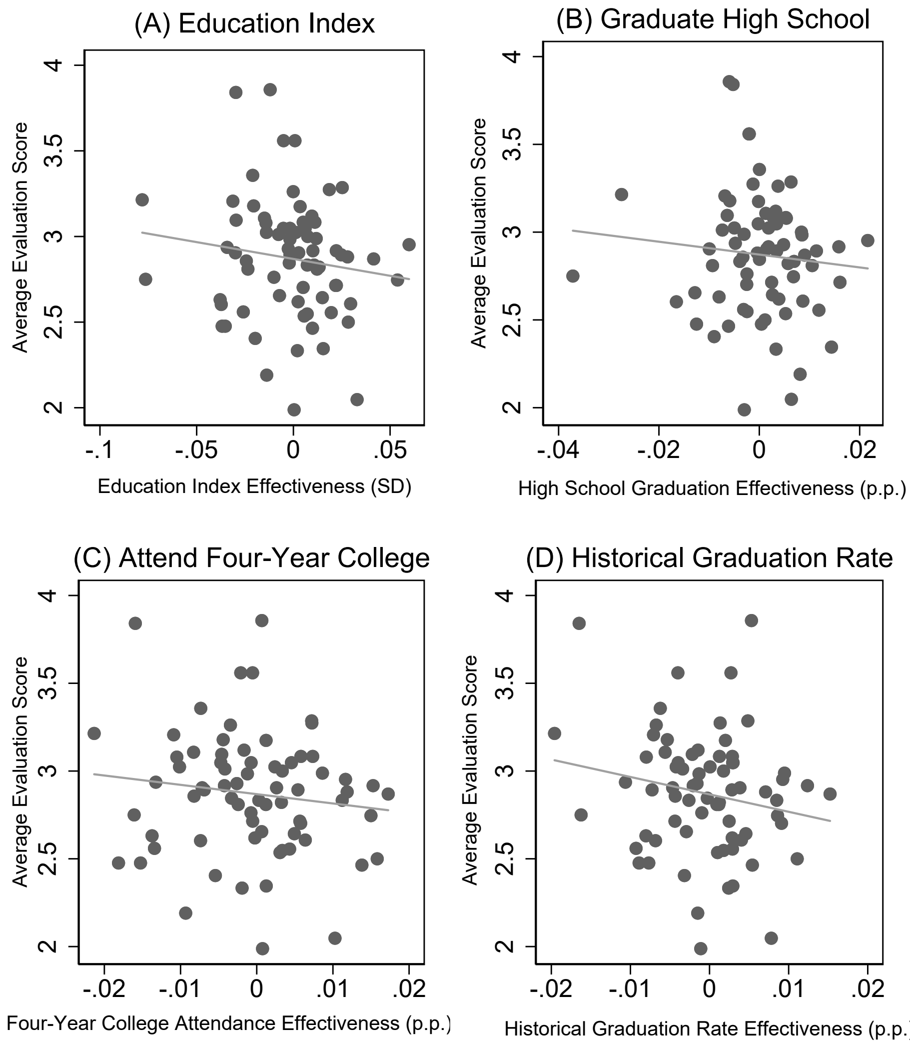
Notes: The figures above show how high school completion (in panels (A) and (C)) or four-year college attendance (in panels (B) and (D)) change when the number of counselors at a school increases (panels (A) and (B) or decreases (panels (C) and (D)). Time 1 on the x-axis is when 12th graders first received or lost an additional counselor. Time 2 is when 11th graders first experienced the change, time 3 for 10th graders, and time 4 for 9th graders. All changes are relative to time 0. The number of counselors in a school must have been constant for at least 2 years prior to the change, and the change must have been sustained for at least 2 years for the change to be included in this event study. Some of the noise at the tails may be due to additional changes to the number of counselors. The x-axis indicates the change in the high school graduation or four-year college enrollment rate, conditional on school fixed effects and year fixed effects. The bars represent 95% confidence intervals.

Figure A.4: Predictive Power of Evaluation Scores for Educational Attainment



Notes: The figures above show the relationship between the quantile of a counselor's average evaluation score and the rate of high school completion (in Panel A) or four-year college attendance (in Panel B). All estimates are relative to counselors in the bottom quintile. These estimates are based on data from Wake County. A counselor's quintile of evaluation score is based on her average score in all years between 2015 and 2018. Counselors are typically rated by principals. They are rated on a scale of 0-4 on five main domains. Their average across these domains is used to generate a cumulative score between 0 and 4. In panel (A) the x-axis is the average effect of counselors on high school graduation and in panel (B) the x-axis indicates counselors' average effects on four-year college attendance. The x-axis is in terms of percentage points and these effects are conditional on school, year, grade and first letter of last name fixed effects plus controls for student demographics, achievement and services received in eighth grade. School fixed effects should also capture rater effects since, in most cases, all counselors in a school will be evaluated by the same person. Four-year college attendance is based on attendance within six months of graduating high school. Here, high school graduation is an indicator for whether the student graduated from a public high school in Wake County, NC. The bars represent 95% confidence intervals.

Figure A.5: Scatterplots of Evaluation Scores and Effectiveness Measures



Notes: The figures above are scatterplots of each counselor's average evaluation score and that counselor's average effectiveness. The y-axes are counselors' average evaluation scores between 2015 and 2018 (from Wake County, NC). The x-axis indicates each counselor's empirical Bayes estimate of effectiveness. Panel (A) is based on effectiveness in terms of the education index. Panel (B) is for effectiveness in terms of high school graduation. Panel (C) is for effectiveness in terms of four-year college attendance and panel (D) is for effectiveness in terms of the historical six-year graduation rate at the college a student attends. Four-year college attendance and historical graduation rate are based on college attendance within six months of graduating high school. In panel (A), effectiveness is in terms of standard deviations. In panels (B)-(D) effectiveness is in terms of percentage points. There is one dot per counselor. These figures are based on counselors from Wake County, NC who were evaluated at least twice between 2015 and 2018 (and who were matched to at least two cohorts of 20 students based on a last name assignment rule). The lines indicate the results from a regression of counselors' average evaluation scores on the measures of effectiveness.

Table A.1: Breakdown of Counselor Time Usage

Activity	% of Time
Postsecondary admission counseling	30%
Choice and scheduling of HS courses	20%
Personal needs counseling	22%
Academic testing	12%
Occupational counseling and job placement	6%
Teaching	5%
Other Activities	5%

Notes: These estimates come from the National Association for College Admission Counseling's 2018 Counseling Trends Survey, as reported in NACAC's 2018 *State of College Admission*.

Table A.2: School Summary Statistics

	All (1)	In Sample (2)	Not in Sample (3)
(A) Demographics and Achievement			
White	0.65	0.82	0.57
African American	0.11	0.04	0.15
Hispanic	0.17	0.08	0.21
Asian	0.04	0.04	0.04
English Language Learner	0.05	0.02	0.07
Students with Disabilities	0.20	0.15	0.22
Free/Reduced Lunch	0.39	0.24	0.47
Accountability Percentile	0.50	0.58	0.45
(B) Location and Size			
Urban	0.22	0.12	0.28
Suburban	0.56	0.66	0.51
Rural	0.20	0.22	0.18
Traditional School	0.78	0.92	0.71
Charter School	0.10	0.03	0.13
Vocational School	0.10	0.05	0.13
Per-Pupil Spending	14,629	13,535	15,249
(C) Postsecondary Plans			
Plan to Attend Four-Year College	0.54	0.65	0.47
Plan to Attend Two-Year College	0.25	0.20	0.28
Plan to Work	0.08	0.07	0.09
Plan to Join Military	0.02	0.02	0.03
N	390	131	259

Notes: Column 1 contains all MA high schools. Column 2 contains all MA high schools in my sample. Column 3 contains all MA high schools not in my sample. My sample is defined as schools where at least two cohorts of twenty students are linked to counselors based on last name assignment rules. This is the sample used to compute measures of counselor effectiveness and the standard deviations of counselor effects. The demographic and achievement data are school averages (or fractions) as reported on the Department of Elementary and Secondary Education's website. Postsecondary plans are based on reports from the 10th grade state exam. These statistics are based on the 2012-2013 school year.

Table A.3: Placebo Tests

	8th Gr. Test
(A) Main Outcomes	
Graduate High School	-0.006
	(0.014)
Attend College	-0.003
	(0.014)
Four-Year College Attendance	0.003
	(0.010)
1st Year Persistence	-0.013
	(0.018)
Historical Graduation Rate	0.005
	(0.012)
(B) Indices	
Composite	-0.003
	(0.014)
Cognitive Skills	-0.003
	(0.009)
Non-Cognitive Skills	-0.014
	(0.013)
Coll Readiness	-0.003
	(0.012)
Coll Selectivity	0.007
	(0.010)
Education	-0.002
	(0.013)
N	142,161

Notes: Heteroskedasticity robust standard errors clustered by counselor and cohort are in parentheses. (*p<.10 **p<.05 *** p<.01). All regressions include fixed effects for the first letter of the student's last name, school, grade, and year (when a student was first assigned to the counselor). Estimates are based on the first counselor to which a student is quasi-randomly assigned. Estimates also contain controls for whether the student took an 8th grade test, English language proficiency, special education receipt, receipt of free or reduced-price lunch, receipt of Title 1 services, existence of a 504 plan, enrollment in 8th grade in an MA public school, days absent, days truant, indicators for race (Black, white, Asian or Hispanic), and gender. The estimates indicate the impact of assignment to a one standard deviation better counselor, in terms of the relevant measure of effectiveness, on eighth grade test scores (in standard deviation units). They are based on the leave-year-out empirical Bayes estimates of effectiveness. College attendance is based on attendance within six months of completing high school. Persistence is an indicator for enrolling in a second year of college. Historical graduation rate refers to the six-year graduation rate at the college a student attends. Historical graduation rate and persistence are zero for students who do not attend college within six months of finishing high school.

Table A.4: Covariance Based Estimates of Variance

	Graduate High School (1)	Attend College (2)	Attend Four-Year College (3)	Historical Graduation Rate (4)	Persist 1st Year (5)	Composite Index (6)
(A) OLS						
Std Dev	0.021	0.016	0.014	0.009	0.013	0.056
P-value	0.00	0.01	0.01	0.25	0.01	0.00
(B) Logit						
Std Dev	0.018	0.016	0.015	.	0.013	.

Notes: The standard deviation estimates above are the square root of covariance of counselors' fixed effects over time. The P-values are based on randomization inference. They indicate the fraction of estimates from randomly re-assigned counselors for which the estimated standard deviations of counselor effects are higher than the estimate in my sample. These estimates incorporate fixed effects for the first letter of the student's last name, school, grade, and year (when a student was first assigned to the counselor) as well as controls for the student's 8th grade test scores, English language proficiency, special education receipt, receipt of free or reduced-price lunch, receipt of Title 1 services, existence of a 504 plan, enrollment in 8th grade in an MA public school, days absent in 8th grade, indicators for race (Black, white, Asian or Hispanic), and gender. Estimates are based off the first counselor to which a student is quasi-randomly assigned. College attendance is based on attendance within six months of completing high school. Persistence is an indicator for enrolling in a second year of college. Historical graduation rate refers to the six-year graduation rate at the college a student attends. Historical graduation rate and persistence are zero for students who do not attend college within six months of finishing high school. The effects in columns 1-5 are in percentage points. Those in column 6 are in standard deviation units.

Table A.5: Randomization-Based Inference on Variance Estimates

	Graduate HS (1)	Attend College (2)	Attend Four-Year (3)	Historical Grad Rate (4)	Persist 1st Year (5)	Education Index (SD) (6)
(A) Estimated Effects						
SD	0.020	0.014	0.017	0.010	0.011	0.040
SE	(0.002)	(0.003)	(0.003)	(0.002)	(0.004)	(0.005)
(B) Randomization Inference						
Mean (of SD)	0.009	0.006	0.007	0.006	0.002	0.015
Std. Dev (of SD)	0.0019	0.0041	0.0041	0.0026	0.0036	0.0071
Min	0.005	0.000	0.000	0.000	0.000	0.000
Max	0.013	0.015	0.014	0.011	0.014	0.028
95th Percentile	0.012	0.012	0.013	0.009	0.009	0.026
99th Percentile	0.013	0.015	0.014	0.011	0.014	0.028
P-value	0.00	0.02	0.00	0.02	0.02	0.00

Notes: The estimates in Panel A are the main results reported in Table 3. They are from models controlling for student demographics, achievement, first letter of last name, cohort and school. Standard errors of the standard deviation estimates are in parentheses. These are obtained directly from the maximum likelihood estimation. Panel (B) contains esimtates from randomization inference. This involves randomly re-assigning counselors (within schools and years) and estimating the variance of these placebo counselors' effects. These estiamtes are based on 100 iterations of random re-assignment. Panel (B) reports the mean standard deviation of counselor effects in these placebo exercises, the standard deviation of thes standard deviations, the maximum and minimum. The p-value is based on the fraction of instances where the estimated standard deviations of counselors' effects in the random re-assignment sample is larger than my estimate of counselor effects in the true sample. The estimates in columns 1-5 are in percentage points. Those in column 6 are in standard deviation units (of the education index). College attendance is based on attendance within six months of completing high school. Persistence is an indicator for enrolling in a second year of college. Historical graduation rate refers to the six-year graduation rate at the college a student attends. Historical graduation rate and persistence are zero for students who do not attend college within six months of finishing high school.

Table A.6: Variance in Outcomes due to Counselors by Grade

	Graduate High School (1)	Attend College (2)	Attend Four-Year College (3)	Historical Graduation Rate (4)	Education Index (5)
(A) Grade 9					
SD	0.021	0.012	0.011	0.005	0.034
	(0.003)	(0.004)	(0.004)	(0.005)	(0.007)
(B) Grade 10					
SD	0.011	0.010	0.009	0.007	0.023
	(0.004)	(0.005)	(0.005)	(0.003)	(0.009)
(C) Grade 11					
SD	0.006	0.000	0.010	0.008	0.019
	(0.006)	(0.000)	(0.005)	(0.003)	(0.010)
(D) Grade 12					
SD	0.015	0.012	0.019	0.011	0.033
	(0.002)	(0.004)	(0.003)	(0.002)	(0.005)

Notes: The SD (standard deviation) is estimated via restricted maximum likelihood from models controlling for students' demographics, achievement, first letter of last name, cohort, and school. Standard errors of the standard deviation estimates are in parentheses. These estimates come from fitting the main model (in Table 3) separately by student grade. Most students have the same counselor for multiple grades. Variation in effects by grades is based on students who do not have the same counselor for all four years. This could be due to students switching schools or counselors entering or leaving a school while a studnet is enrolled. The effects in columns 1-4 are in percentage points. Those in column 5 are in standard deviation units (of the education index). College attendance is based on attendance within six months of completing high school. Historical graduation rate refers to the six-year graduation rate at the college a student attends. Historical graduation rate and persistence are zero for students who do not attend college within six months of finishing high school.

Table A.7: Variance Decomposition: Standard Deviations of Effects on Educational Attainment

	Graduate HS (1)	Attend College (2)	Attend Four-Year (3)	Historical Grad Rate (4)	Persist 1st Year (5)	Edu Index (SD) (6)	Composite Index (SD) (7)	8th Grade Test (8)
Total SD	0.357	0.455	0.453	0.292	0.470	0.871	0.786	0.662
Counselor SD	0.020	0.014	0.017	0.010	0.011	0.041	0.052	0.000
Counselor x Class SD	0.037	0.029	0.028	0.019	0.028	0.071	0.103	0.076
Individual SD	0.301	0.413	0.408	0.262	0.431	0.759	0.631	0.586
N Counselors	510	510	510	510	510	510	510	510
N Students	142,161	142,161	142,161	142,161	121,041	142,161	142,161	142,161

Notes: The standard deviations above are directly estimated via restricted maximum likelihood from a multi-level model where counselor effects and counselor by cohort shocks are treated as random. These models include controls for students' demographics, eighth grade achievement and services received, first letter of last name, grade, cohort, and school. The effects in columns 1-5 are in percentage points. Those in column 6-8 are in standard deviation units. College attendance is based on attendance within six months of completing high school. Persistence is an indicator for enrolling in a second year of college. Historical graduation rate refers to the six-year graduation rate at the college a student attends. Historical graduation rate and persistence are zero for students who do not attend college within six months of finishing high school.

Table A.8: Measurement Error in Counselor Fixed Effects

	Indices							
	Composite	Cognitive Skills	Non-Cognitive Skills	College Readiness	College Selectivity	Education	Graduate High School	Attend Four-Year
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\hat{Var}(\mu_{jy})$	0.0027	0.0002	0.0020	0.0063	0.0008	0.0016	0.0004	0.0003
$Var(\bar{\mu}_{jy})$	0.0048	0.0038	0.0064	0.0096	0.0042	0.0043	0.0009	0.0010
ρ_{FE}	0.563	0.053	0.313	0.656	0.190	0.372	0.444	0.291

Notes: $\hat{Var}(\mu_{jy})$ is the estimated variance due to counselors from the multi-level model with counselor random effects. These estimates condition on student demographics, eighth grade achievement and services received, school, grade, cohort and first letter of last name fixed effects as well as counselor by cohort shocks. $Var(\bar{\mu}_{jy})$ is the variance of the counselor fixed effect estimates. The fixed effects condition on student demographics, eighth grade achievement and services received, school, grade, cohort and first letter of last name fixed effects but they do not account for measurement error. ρ_{FE} is the value in row 1 divided by the value in row 2. Formally, this is the ratio of the true variance due to counselors divided by the observed variance of the counselor fixed effects. The estimates in columns 1-6 are in standard deviation units and those in columns 7 and 8 are in percentage points. College attendance is based on attendance within six months of completing high school.

Table A.9: Impact of a Predicted 1 SD Better Counselor by Additional Subgroups

	Graduate High School (1)	Attend College (2)	Attend Four-Year College (3)	Historical Graduation Rate (4)	Persist 1st Year (5)	Education Index (6)
(A) By Gender						
Male	0.024***	0.014*	0.013**	0.008**	0.010	0.043***
	(0.006)	(0.007)	(0.005)	(0.003)	(0.006)	(0.012)
Female	0.017***	0.016***	0.021***	0.017***	0.019***	0.045***
	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.009)
P-value Diff	0.09	0.77	0.14	0.10	0.20	0.77
Male Mean	0.85	0.61	0.48	0.34	0.51	0.15
Female Mean	0.89	0.72	0.59	0.42	0.63	0.37
(B) By Prior Achievement						
Low Test	0.035***	0.027***	0.024***	0.012***	0.025***	0.072***
	(0.008)	(0.007)	(0.006)	(0.003)	(0.005)	(0.015)
Med Test	0.010	0.010	0.023**	0.020***	0.013	0.036*
	(0.006)	(0.009)	(0.009)	(0.005)	(0.011)	(0.019)
High Test	-0.001	-0.007	-0.007	0.004	-0.009	-0.012
	(0.004)	(0.008)	(0.008)	(0.004)	(0.009)	(0.016)
Low Test Mean	0.77	0.47	0.28	0.18	0.36	-0.20
Med Test Mean	0.93	0.75	0.62	0.41	0.64	0.44
High Test Mean	0.96	0.86	0.81	0.62	0.79	0.73
(C) By Location						
Rural	0.018**	0.008	0.013*	0.011***	0.007	0.032**
	(0.006)	(0.005)	(0.007)	(0.003)	(0.005)	(0.013)
Suburban	0.017***	0.016**	0.022***	0.016***	0.015**	0.047***
	(0.004)	(0.006)	(0.004)	(0.003)	(0.005)	(0.009)
Urban	0.025**	0.019*	0.014*	0.010**	0.019*	0.048**
	(0.011)	(0.008)	(0.007)	(0.004)	(0.008)	(0.019)
Rural Mean	0.88	0.68	0.56	0.59	0.41	0.31
Suburban Mean	0.89	0.70	0.59	0.61	0.42	0.36
Urban Mean	0.77	0.50	0.30	0.38	0.20	-0.15
N	138,774	138,774	138,774	138,774	117,895	138,774

Notes: Heteroskedasticity robust standard errors clustered by counselor and cohort are in parentheses. (*p<.10 **p<.05 *** p<.01). All regressions include fixed effects for the first letter of the student's last name, school, grade, and year (when a student was first assigned to the counselor). Estimates are based on the first counselor to which a student is quasi-randomly assigned. Estimates also contain controls for the student's 8th grade test scores, English language proficiency, special education receipt, receipt of free or reduced price lunch, receipt of Title 1 services, existence of a 504 plan, enrollment in 8th grade in an MA public school, days absent, days truant, indicators for race (Black, white, Asian or Hispanic), and gender. Panel (A) divides students by their gender. Panel (B) divides students by their 8th grade test scores. Here, students are split into terciles based on whether their test score is in the bottom, middle or top third of students *in my sample*. Students with scores in the bottom third are defined as low test students. Panel (C) shows estimates separately by the urbanicity of where a student's high school is located. These classifications are based on the NCES urbanicity codes. Counselor effectiveness is defined using the composite index of effectiveness and the leave-year-out empirical Bayes estimates of effectiveness. College attendance is based on attendance within six months of completing high school. Persistence is an indicator for enrolling in a second year of college. Historical graduation rate refers to the six-year graduation rate at the college a student attends. Historical graduation rate and persistence are zero for students who do not attend college within six months of finishing high school.

Table A.10: Leave-Year-Out Estimates from Kane & Staiger Method

	Relevant Indicator (1)	Graduate High School (2)	Attend College (3)	Attend Four-Year College (4)	Historical Graduation Rate (5)	Persist 1st Year (6)	Education Index (7)
(A) Composite Index							
Counselor Effectiveness (SD)	0.088***	0.024***	0.016**	0.018**	0.013***	0.015**	0.088***
	(0.022)	(0.007)	(0.007)	(0.005)	(0.003)	(0.006)	(0.022)
(B) Education Index							
Counselor Effectiveness (SD)	0.056***	0.021**	0.022***	0.023***	0.014***	0.023***	0.062***
	(0.014)	(0.007)	(0.006)	(0.005)	(0.003)	(0.006)	(0.012)
(C) Intermediate Indices							
Cognitive Skills	0.037	-0.011	-0.011	0.006	0.002	-0.012*	-0.020*
	(0.022)	(0.006)	(0.007)	(0.006)	(0.003)	(0.006)	(0.009)
Non-Cognitive Skills	0.099***	0.001	0.003	-0.001	-0.001	0.003	0.028*
	(0.021)	(0.006)	(0.005)	(0.004)	(0.002)	(0.006)	(0.013)
College Readiness	0.126***	0.022***	0.008	0.008*	0.008**	0.008	0.066***
	(0.030)	(0.006)	(0.005)	(0.004)	(0.003)	(0.006)	(0.020)
College Quality	0.059***	0.005	0.016*	0.022***	0.014**	0.017***	0.006
	(0.017)	(0.005)	(0.007)	(0.007)	(0.006)	(0.005)	(0.016)
(D) Direct VA							
Effectiveness (SD) for Outcome	0.088***	0.021***	0.025**	0.037***	0.022***	0.024	0.056***
	(0.022)	(0.006)	(0.008)	(0.007)	(0.005)	(0.018)	(0.014)
N	142,033	142,161	142,161	142,161	142,161	116,314	142,161

Notes: Heteroskedasticity robust standard errors clustered by counselor are in parentheses. (*p<.10 **p<.05 *** p<.01). All regressions include fixed effects for the first letter of the student's last name, school, grade, and year (when a student was first assigned to the counselor). Estimates are based off the first counselor to which a student is quasi-randomly assigned. Estimates also controls for the student's 8th grade English language proficiency, special education receipt, receipt of free or reduced-price lunch, receipt of Title 1 services, existence of a 504 plan, enrollment in 8th grade in an MA public school, days absent in 8th grade, indicators for race (Black, white, Asian or Hispanic), and gender. Counselor effectiveness is in standard deviation units and is based on the leave-year-out empirical Bayes estimates of effectiveness. Here these estimates are calculated using the covariance based approach described in Kane & Staiger (2008). The estimates indicate how much a predicted one standard deviation better counselor increases educational attainment. The effects in columns 2-6 are in percentage points. Those in column 7 are in standard deviation units (of the education index). The estimates in column (1) are in standard deviation units and they indicate the effect on the effectiveness-specific outcome defined on the left. For instance, in panel (A), column (1) indicates how much a one standard deviation predicted better counselor in terms of the composite index increases the composite index measure of student outcomes. Panel (D) indicates how much a one standard deviation better counselor (on the outcome defined at the top of the column) increases that specific outcome. College attendance is based on attendance within six months of completing high school. Persistence is an indicator for enrolling in a second year of college. Historical graduation rate refers to the six-year graduation rate at the college a student attends. Historical graduation rate and persistence are zero for students who do not attend college within six months of finishing high school.

Table A.11: Leave-Year-Out Estimates from Chetty, Friedman & Rockoff Method

	Relevant Indicator (1)	Graduate High School (2)	Attend College (3)	Attend Four-Year College (4)	Historical Graduation Rate (5)	Persist 1st Year (6)	Education Index (7)
(A) Composite Index							
Counselor Effectiveness (SD)	0.081**	0.020***	0.014*	0.013*	0.012**	0.013*	0.039**
	(0.029)	(0.006)	(0.007)	(0.006)	(0.004)	(0.006)	(0.015)
(B) Education Index							
Counselor Effectiveness (SD)	0.035***	0.018***	0.014***	0.011***	0.008***	0.014***	0.035***
	(0.007)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.007)
(C) Intermediate Indices							
Cognitive Skills	0.030	-0.008	-0.006	-0.001	-0.003	-0.003	-0.013
	(0.018)	(0.006)	(0.004)	(0.004)	(0.003)	(0.004)	(0.009)
Non-Cognitive Skills	0.087***	0.005	0.004	0.000	0.002	0.003	0.008
	(0.014)	(0.003)	(0.002)	(0.002)	(0.001)	(0.002)	(0.005)
College Readiness	0.073**	0.006*	0.006	0.008**	0.007***	0.007	0.016*
	(0.028)	(0.003)	(0.004)	(0.003)	(0.002)	(0.006)	(0.008)
College Quality	0.029**	0.012***	0.012***	0.012***	0.011***	0.012***	0.031***
	(0.010)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)	(0.005)
(D) Direct VA							
Effectiveness (SD) for Outcome	0.081**	0.018***	0.013**	0.007*	0.008*	0.016**	0.035***
	(0.029)	(0.005)	(0.004)	(0.004)	(0.004)	(0.007)	(0.007)
N	142,161	142,161	142,161	142,161	142,161	116,314	142,161

Notes: Heteroskedasticity robust standard errors clustered by counselor are in parentheses. (*p<.10 **p<.05 *** p<.01). All regressions include fixed effects for the first letter of the student's last name, each school, grade, and year (when a student was first assigned to the counselor). Estimates are based off the first counselor to which a student is quasi-randomly assigned. Estimates also controls for the student's 8th grade English language proficiency, special education receipt, receipt of free or reduced-price lunch, receipt of Title 1 services, existence of a 504 plan, enrollment in 8th grade in an MA public school, days absent in 8th grade, indicators for race (Black, white, Asian or Hispanic), and gender. Counselor effectiveness is in standard deviation units and is based on the leave-year-out empirical Bayes estimates of effectiveness. Here these estimates are calculated using the approach described in Chetty, Friedman & Rockoff (2014a). The estimates indicate how much a predicted one standard deviation better counselor increases educational attainment. The effects in columns 2-6 are in percentage points. Those in column 7 are in standard deviation units (of the education index). The estimates in column (1) are in standard deviation units and they indicate the effect on the effectiveness-specific outcome defined on the left. For instance, in panel (A), column (1) indicates how much a one standard deviation predicted better counselor in terms of the composite index increases the composite index measure of student outcomes. Panel (D) indicates how much a one standard deviation better counselor (on the outcome defined at the top of the column) increases that specific outcome. College attendance is based on attendance within six months of completing high school. Persistence is an indicator for enrolling in a second year of college. Historical graduation rate refers to the six-year graduation rate at the college a student attends. Historical graduation rate and persistence are zero for students who do not attend college within six months of finishing high school.

Table A.12: Counselor Effects with Logit Specification (Odds Ratios)

	Graduate High School (1)	Attend College (2)	Attend Four-Year College (3)	Persist 1st Year (4)
(A) Composite Index				
Composite Index	1.182***	1.079***	1.105***	1.076***
	(0.031)	(0.018)	(0.021)	(0.020)
(B) Additional Indices				
Cognitive Skills	0.960	0.934**	0.996	0.953*
	(0.049)	(0.028)	(0.030)	(0.027)
Non-Cognitive Skills	1.087***	1.042**	1.036*	1.034*
	(0.027)	(0.019)	(0.021)	(0.019)
College Readiness	1.163***	1.067***	1.079***	1.069***
	(0.028)	(0.016)	(0.019)	(0.018)
College Selectivity	1.163***	1.085***	1.128***	1.081***
	(0.052)	(0.028)	(0.029)	(0.028)
Education	1.186***	1.108***	1.132***	1.109***
	(0.037)	(0.022)	(0.024)	(0.024)
(C) Education Outcomes				
Grad HS	1.151***			
	(0.033)			
Attend Coll		1.083***		
		(0.026)		
Attend 4-Yr			1.141***	
			(0.024)	
Persist 1st Yr				1.034
				(0.034)
N	142,161	142,161	142,161	121,041

Notes: Heteroskedasticity robust standard errors clustered by counselor and cohort are in parentheses. (*p<.10 **p<.05 *** p<.01). All regressions include fixed effects for the first letter of the student's last name, each school, grade, and year (when a student was first assigned to the counselor). Estimates are based on the first counselor to which a student is quasi-randomly assigned. Estimates also contain controls for the student's 8th grade test scores, English language proficiency, special education receipt, receipt of free or reduced-price lunch, receipt of Title 1 services, existence of a 504 plan, enrollment in 8th grade in an MA public school, days absent, days truant, indicators for race (Black, white, Asian or Hispanic), and gender. These estimates are from a logistic regression of binary student outcomes on counselors' predicted effectiveness, as defined by the leave-year out empirical Bayes estimates. All estimates are from regressions of an outcome on an individual index of effectiveness. Counselor effectiveness is in standard deviation units. The estimates indicate how much a predicted one standard deviation better counselor increases educational attainment. The effects are in percentage points. College attendance is based on attendance within six months of completing high school. Persistence is an indicator for enrolling in a second year of college. Persistence rates are zero for students who do not attend college within six months of finishing high school.

Table A.13: Correlation and Average Differences Between Effectiveness on Different Dimensions

	Indices						
	Composite	Non-Cognitive Skills	Cognitive Skills	College Readiness	College Selectivity	Education	Highly Selective Coll
Composite Index		0.761***	0.783***	0.570	0.450	0.284	0.806***
Non-Cognitive SKills	0.467***		0.757***	0.651	0.891***	0.794***	0.956***
	(0.054)						
Cognitive Skills	0.262***	0.024		0.728***	0.854***	0.801***	0.969***
	(0.065)	(0.123)					
College Readiness	0.671***	0.509***	0.192*		0.687	0.607	0.889***
	(0.031)	(0.035)	(0.108)				
College Selectivity	0.815***	0.183***	0.276***	0.467***		0.631	0.585
	(0.024)	(0.039)	(0.041)	(0.040)			
Education	0.936***	0.349***	0.239***	0.627***	0.642***		0.959***
	(0.013)	(0.031)	(0.075)	(0.029)	(0.025)		
Highly Selective Coll	0.394***	-0.003	0.097***	0.142	0.698***	0.162***	
	(0.029)	(0.027)	(0.029)	(0.028)	(0.021)	(0.030)	

Notes: Raw correlations between the empirical Bayes estimates of counselor effectiveness are in the lower triangle. These are based on all students quasi-randomly assigned to a counselor. (*p<.10 **p<.05 *** p<.01). Standard errors are in parentheses. The upper triangle indicates the average difference in a counselor's effects on the two measures on the top and left of the table. These are the absolute value of the differences in a counselor's estimated effect for these outcomes, in standard deviation units. The stars in the upper triangle are from a chi-square test for whether the differences are statistically significant from zero. All measures of counselor effectiveness are estimated via restricted maximum likelihood in a multilevel model where counselor effects and counselor by cohort shocks are treated as random. They include fixed effects for the first letter of the student's last name, school, grade, and year (when a student was first assigned to the counselor), controls for the student's 8th grade test scores, English language proficiency, special education receipt, receipt of free or reduced-price lunch, receipt of Title 1 services, existence of a 504 plan, enrollment in 8th grade in an MA public school, days absent, days truant, indicators for race (Black, white, Asian or Hispanic), and gender. Estimates are based on the first counselor to which a student is quasi-randomly assigned. Highly selective coll is an indicator for whether the student attends a highly selective college as defined by Barron's 2009 rankings.

Table A.14: Impact of Additional Counselor Characteristics

	Graduate High School (1)	Attend College (2)	Attend Four-Year College (3)	Historical Graduation Rate (4)	Persist 1st Year (5)
(A) Gender Match					
Gender Match	-0.004*	-0.004	-0.004	0.000	-0.002
	(0.002)	(0.003)	(0.003)	(0.002)	(0.004)
Female Match	-0.001	-0.003	0.000	0.002	0.000
	(0.003)	(0.005)	(0.004)	(0.003)	(0.005)
Male Match	-0.008*	-0.006	-0.010**	-0.002	-0.005
	(0.004)	(0.005)	(0.004)	(0.003)	(0.005)
(B) Educator Experience					
Teacher	-0.014**	-0.008	-0.005	-0.006	-0.004
	(0.006)	(0.006)	(0.006)	(0.004)	(0.006)
Supervisor	-0.004	-0.008	-0.020***	-0.012**	-0.008
	(0.005)	(0.007)	(0.008)	(0.005)	(0.006)
N	142,275	142,275	142,275	142,275	118,307

Notes: Heteroskedasticity robust standard errors clustered by counselor in parentheses. (*p<.10 **p<.05 *** p<.01). All regressions include letter of last name, school, cohort, and grade fixed effects as well as controls for students' and counselors' race and gender. They also include controls for the student's 8th grade test scores, English language proficiency, special education receipt, receipt of free or reduced-price lunch, receipt of Title 1 services, existence of a 504 plan, enrollment in 8th grade in an MA public school, days absent, and days truant. Estimates are based on the first counselor to which a student is quasi-randomly assigned. College attendance is based on attendance within six months of completing high school. Persistence is an indicator for enrolling in a second year of college. Historical graduation rate refers to the six-year graduation rate at the college a student attends. Historical graduation rate and persistence are zero for students who do not attend college within six months of finishing high school. Teacher is an indicator for whether the counselor has a teaching license. Supervisor is an indicator for whether the counselor is a counseling supervisor while the student is assigned to that counselor.

Table A.15: Counselors' College Experiences and the College Outcomes of their Students

	Attend Four-Year (1)	Attend In-State (2)	Attend Public (3)	Attend Large (4)	Small Private (5)	Historical Grad Rate (6)	Highly Selective (7)	Elite (8)
(A) Overall								
Coll in MA	0.010	0.020***	0.007	-0.002	0.008	0.009**	0.002	0.007**
	(0.007)	(0.007)	(0.008)	(0.005)	(0.005)	(0.004)	(0.003)	(0.003)
Large Coll	0.013*	0.001	-0.005	0.015***	0.004	0.006	0.009***	0.000
	(0.007)	(0.008)	(0.008)	(0.005)	(0.006)	(0.004)	(0.003)	(0.002)
Small Priv Coll	0.005	0.002	0.006	-0.003	-0.001	-0.001	-0.002	-0.001
	(0.007)	(0.009)	(0.007)	(0.006)	(0.005)	(0.004)	(0.003)	(0.002)
Public Coll	0.007	0.009	0.008	0.001	-0.000	0.005	0.001	0.002
	(0.007)	(0.007)	(0.006)	(0.006)	(0.005)	(0.005)	(0.004)	(0.002)
Private Coll	-0.007	-0.009	-0.008	-0.001	0.000	-0.005	-0.001	-0.002
	(0.007)	(0.007)	(0.006)	(0.006)	(0.005)	(0.005)	(0.004)	(0.002)
High Sel. Coll	-0.009	0.000	-0.009	-0.002	0.002	-0.007	-0.000	0.004
	(0.009)	(0.007)	(0.007)	(0.009)	(0.005)	(0.005)	(0.005)	(0.004)
Elite Coll	-0.017	-0.016*	-0.013*	-0.003	-0.007	-0.005	0.006	0.014**
	(0.012)	(0.010)	(0.007)	(0.009)	(0.007)	(0.006)	(0.008)	(0.006)
N	30,241	30,232	30,232	30,241	30,232	30,241	30,241	30,241
(B) Among College Attendees								
Coll in MA	0.000	0.010	-0.008	-0.002	0.005	0.003	0.005	0.016***
	(.)	(0.009)	(0.010)	(0.009)	(0.009)	(0.003)	(0.006)	(0.005)
Large Coll	0.000	0.011	0.007	0.019**	-0.005	0.003	0.011**	-0.003
	(.)	(0.009)	(0.008)	(0.008)	(0.009)	(0.002)	(0.005)	(0.004)
Small Priv Coll	0.000	-0.010	-0.010	-0.001	-0.002	-0.002	-0.004	-0.002
	(.)	(0.010)	(0.009)	(0.009)	(0.008)	(0.003)	(0.006)	(0.005)
Public Coll	0.000	0.008	0.014*	-0.003	-0.008	-0.001	0.001	0.004
	(.)	(0.007)	(0.007)	(0.009)	(0.006)	(0.003)	(0.006)	(0.004)
Private Coll	0.000	-0.008	-0.014*	0.003	0.008	0.001	-0.001	-0.004
	(.)	(0.007)	(0.007)	(0.009)	(0.006)	(0.003)	(0.006)	(0.004)
High Sel. Coll	0.000	0.005	-0.005	0.003	0.005	-0.002	0.000	0.006
	(.)	(0.009)	(0.008)	(0.012)	(0.008)	(0.003)	(0.007)	(0.005)
Elite Coll	0.000	-0.017	-0.006	0.003	-0.005	0.000	0.012	0.022***
	(.)	(0.012)	(0.010)	(0.011)	(0.010)	(0.004)	(0.009)	(0.007)
N	16,194	16,194	16,194	16,194	16,194	16,194	16,194	16,194

Notes: Heteroskedasticity robust standard errors clustered by counselor in parentheses. (*p<.10 **p<.05 *** p<.01). All regressions include letter of last name, school, cohort, and grade fixed effects as well as controls for students' and counselors' race and gender. They also include controls for the student's 8th grade test scores, English language proficiency, special education receipt, receipt of free or reduced-price lunch, receipt of Title 1 services, existence of a 504 plan, enrollment in 8th grade in an MA public school, days absent, and days truant. Estimates are based on the first counselor to which a student is quasi-randomly assigned. These estimates indicate the relationship between the type of undergraduate college a counselor attended (on the left) and the type of college a student attends (on the top). Counselor education data are self-reported by about 20% of counselors. Panel (A) shows where all students attend college, with college characteristics imputed as zero for students who do not attend college within six months of graduating high school. Panel (B) is restricted to students who attended college within six months of graduating high school. College selectivity is defined using Barron's 2009 rankings of selectivity. Historical graduation rate refers to the six year graduation rate at the college a student attends. Large is defined as a college with more than 10,000 undergraduate students. Small private is defined as a private college with less than 5,000 undergraduate students.

Table A.16: Predictors of Supervisor Promotion

	Effectiveness (1)	Demographics (2)	Experience (3)	All (4)
Cognitive Skills	-0.021			-0.016
	(0.016)			(0.016)
Non-Cognitive Skills	0.028			0.027
	(0.017)			(0.017)
Coll Readiness	0.001			0.001
	(0.020)			(0.020)
Coll Selectivity	-0.003			-0.006
	(0.020)			(0.020)
Education Index	-0.010			-0.010
	(0.022)			(0.022)
Male		-0.061*		-0.061*
		(0.034)		(0.034)
White		0.098		0.077
		(0.166)		(0.168)
Black		-0.037		-0.075
		(0.207)		(0.210)
Hispanic		-0.031		-0.094
		(0.233)		(0.237)
Teacher			-0.138**	-0.134**
			(0.056)	(0.056)
Starting Year			-0.004*	-0.004*
			(0.002)	(0.002)
N	478	478	478	478

Notes: (*p<.10 **p<.05 *** p<.01). Estimates are from a regression of an indicator for ever serving as a counseling supervisor on the dependent variables indicated in the table. Effectiveness measures are the empirical Bayes estimates of counselor effectiveness (in standard deviations). Teacher is an indicator for whether the counselor has a teaching license. Starting year indicates the first year the counselor appeared in the Massachusetts HR data as a counselor.

Table A.17: Standard Deviations of Counselor Effects in Wake County

	Graduate High School (1)	Attend College (2)	Attend Four-Year College (3)	Historical Graduation Rate (4)	Persist 1st Year (5)	Education Index (6)
Standard Deviation	0.015	0.016	0.018	0.012	0.015	0.040
	(0.009)	(0.009)	(0.007)	(0.004)	(0.010)	(0.015)
N Counselors	154	154	154	154	154	154
N Students	95,530	95,530	95,530	95,530	85,346	95,530

Notes: The estimates above are the standard deviations of counselors' effects in Wake County, NC. They are estimated from a multi-level model with random effects for counselors and counselor by cohort shocks. Standard errors of the standard deviation estimates are in parentheses. These are obtained directly from the maximum likelihood estimation. All estimates are from models which include fixed effects for the first letter of the student's last name, school, grade, and year (when a student was first assigned to the counselor), as well as random effect parameters for counselor by cohort shocks. Estimates are based on the first counselor to which a student is quasi-randomly assigned. Estimates also contain controls for the student's 8th grade test scores, English language proficiency, special education receipt, receipt of free or reduced-price lunch, enrollment in 8th grade in a Wake County public school, days absent, days truant, indicators for race (Black, white, Asian or Hispanic), and gender. The estimates in columns 1-5 are in percentage points and those in column 6 are in standard deviation units. College attendance is based on attendance within six months of completing high school. Persistence is an indicator for enrolling in a second year of college. Historical graduation rate refers to the six-year graduation rate at the college a student attends. Historical graduation rate and persistence are zero for students who do not attend college within six months of finishing high school.

Table A.18: Predictive Validity of Counselor Effects in Wake County

	Graduate High School (1)	Attend College (2)	Attend Attend Four-Year (3)	Historical Graduation Rate (4)	Persist 1st Year (5)	Education Index (6)
(A) Unit Increase						
Predicted Effect on Outcome	0.789	0.408	0.535	0.561	0.000	0.537
	(0.560)	(0.627)	(0.451)	(0.419)	(0.671)	(0.455)
(B) SD Increase						
Predicted Effect on Outcome	0.004	0.002	0.003	0.003	0.001	0.008
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.007)
Predicted Effect on Edu Index	0.004	0.004	0.003	0.002	0.004	0.008
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.007)
N	96,532	96,532	96,532	96,532	86,303	96,532

Notes: Heteroskedasticity robust standard errors clustered by counselor are in parentheses. (*p<.10 **p<.05 *** p<.01). All regressions include fixed effects for the first letter of the student's last name, school and grade by year (when a student was first assigned to the counselor). Estimates are based off the first counselor to which a student is quasi-randomly assigned. They also contain controls for the student's 8th grade test scores, English language proficiency, special education receipt, receipt of free or reduced-price lunch, enrollment in 8th grade in a Wake County public school, days absent, days truant, indicators for race (Black, white, Asian or Hispanic), and gender. The estimates in columns 1-5 are in percentage points and those in column 6 are in standard deviation units. The estimates in panel (A) indicate the effect of a one unit better counselor in Wake County, NC based on the leave-year-out empirical Bayes estimates of counselor effectiveness. The estimates in panel (B) indicate the effect of a one standard deviation better counselor as defined using the standard deviations of counselor effects in Table 17. In Panel (B) counselor effectiveness is defined both in terms of predicted effect on the relevant outcome (at the top of the table) and in terms of the education index. College attendance is based on attendance within six months of completing high school. Persistence is an indicator for enrolling in a second year of college. Historical graduation rate refers to the six-year graduation rate at the college a student attends. Historical graduation rate and persistence are zero for students who do not attend college within six months of finishing high school.

Table A.19: Correlation of Counselor Effects & Observation Ratings in Wake County

	Education Index (1)	Graduate High School (2)	Attend College (3)	Attend Four-Year College (4)	Historical Graduation Rate (5)	Evaluation Rating (6)
Effect on:						
Education Index	1					
Graduate High School	0.734	1				
Attend College	0.937	0.594	1			
Attend Four-Year	0.883	0.413	0.780	1		
Historical Graduation Rate	0.836	0.473	0.691	0.926	1	
Evaluation Rating	-0.146	-0.124	-0.148	-0.104	-0.142	1

Notes: The above estimates are the correlations of the empirical Bayes estimates of counselor effects (in Wake County, NC) and their average evaluation ratings. Average evaluation ratings are only used for counselors evaluated in at least two years between 2015 and 2018 (to improve the precision of my estimates). Counselors are typically evaluated by principals in Wake County. Counselors effects are in standard deviations and the evaluation ratings are on a scale of 0 to 4. College attendance is based on attendance within six months of completing high school. Persistence is an indicator for enrolling in a second year of college. Historical graduation rate refers to the six-year graduation rate at the college a student attends. Historical graduation rate and persistence are zero for students who do not attend college within six months of finishing high school.