Beyond Teachers: Estimating Individual Guidance Counselors' Effects on Educational Attainment

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Abstract

Counselors are a common school resource for students navigating complicated and consequential education choices. I estimate counselors' causal effects using quasi-random assignment policies in Massachusetts. Counselors vary substantially in their effectiveness at increasing high school graduation and college attendance, selectivity, and persistence. Counselor effects on educational attainment are similar in magnitude to teacher effects, but they flow through improved information and assistance, rather than through cognitive or non-cognitive skill development. Counselor effectiveness is most important for low-income and low-achieving students. 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 schoolers face hundreds of choices with long-term consequences for educational attainment and the labor market. 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 schools 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 secondary and postsecondary pathways. In the U.S., 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 near 250 high schoolers, 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. 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 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 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.

[1] I refer to general high school counselors as guidance counselors since it is the term used by many schools in my sample and it clarifies the type of counselor on which I am focused. Most prefer to be called school counselors: `https://www.schoolcounselor.org/asca/media/asca/Careers-Roles/GuidanceCounselorvsSchoolCounselor.pdf`.

[2] In 2017, the common core of data indicated that there was one secondary school counselor per 237 students, but this may understate caseloads since it includes counselors who are not guidance counselors. 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.

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 the assignment rules as an instrument and controlling for the first letter of the student's last name, year, school, demographics, and eighth grade test scores. 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 significant. Counselors also impact suspensions, AP and SAT test-taking, the type of college a student attends and college majors. Effective counselors can also be identified out of sample and with a composite measure of effectiveness. Assignment to a counselor predicted to be one standard deviation above average (based on effects in other years) increases high school graduation and college attendance by two percentage points.

Second, counselor assignment matters most for students who are low-achieving or 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). For high achievers, counselors are primarily important for increasing college selectivity. In general, good counselors improve all measures of educational attainment.

Third, counselor effects on educational attainment appear driven by the information and direct assistance they provide students rather than through short-term skill development. Counselors' short-term effects on cognitive and non-cognitive skills are not predictive of longer-term outcomes. Rather, counselors' largest measurable effects are on college readiness and selectivity, and their effectiveness on these dimensions is most predictive of 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, 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 other counselors. These locally educated counselors may know more about local college options or be more familiar with state graduation requirements and 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 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

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

impact students, the variation across counselors in their effectiveness, and the characteristics of effective counselors. Prior work shows that increasing access to school counselors, through smaller caseloads, improves elementary students' test scores and behavior, and 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 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 effectiveness, perhaps because its counselors follow a very standardized protocol (Barr & Castleman, 2019).

The quantitative evidence I present confirms the narratives from qualitative research documenting the challenges faced by counselors at under-resourced schools and the potential for counselors to impact individual student choices (McDonough, 1997; Perna, Rowan-Kenyon & Thomas, 2008; Sattin-Bajaj et al, 2018; Stephan & Rosenbaum, 2013). This 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 education 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 improve 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 about education production that are difficult to study in the teacher setting. I show that despite many diverse responsibilities, counselors do not tend to specialize in certain areas, and that their effects on long-term outcomes are not just through their impacts on short-term skill development.

A one standard deviation improvement in counselor effectiveness has a similar effect on high school completion and college outcomes to a one standard deviation improvement in teacher effectiveness. 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; Jackson, 2018). While existing estimates likely understate teachers' full 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 fewer counselors than teachers, and many counselors receive 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 counselors may be an important channel through which students receive such guidance (Bettinger et al, 2012; Carrell & Sacerdote, 2017; Goodman et al, 2019; Mulhern, 2020). 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 technology or siblings. On a large scale, counselors' capacity to impact educational attainment may be greater than prior interventions because nearly every high schooler has 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 shows how counselor effectiveness varies with observable characteristics. Section 7 compares the importance of counselor effectiveness to that of caseloads, teachers and other forms of postsecondary guidance. Section 8 provides evidence from Wake County, NC on the external validity of the Massachusetts estimates. Section 9 concludes.

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

2 Background and Theoretical Framework

2.1 What do High School Counselors Do?

National survey data 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).[6] Given these responsibilities, and prior models of educators' effects, I focus on four main channels through which counselors are likely to influence human capital accumulation and educational attainment. The first two channels build directly on the teacher literature (e.g. Jackson, 2018) and I add a third and fourth channel to encompass responsibilities that are more unique to counselors.

1. **Cognitive Skills:** Counselors can influence cognitive skills, or academic achievement, by influencing which courses students take, their teacher assignments, and access to services such as special education or English language support. Course scheduling is a key responsibility for counselors and prior research shows that course and teacher selection influence academic achievement and educational attainment (Chetty, Friedman, & Rockoff, 2014b; Jackson, 2018; Smith, Hurwitz & Avery, 2017).

2. **Non-cognitive Skills:** Counselors may influence non-cognitive skills, such as behavior and soft skills, through mental health counseling, disciplinary actions, and general support for dealing with the challenges of high school. Improving student behavior or removing disruptive peers can influence educational attainment, 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 classes by increasing their capacity to concentrate, reducing the need for disciplinary actions or increasing attendance (Heller et al, 2017; Schwartz & Rothbart, 2020).

3. **Information:** In their advising roles, counselors may provide information about postsecondary education and labor market options. This might cover the costs and benefits of

[6] This is based on the 2018 "National Association for College Admission Counseling" Counseling Trends Survey. Counselors' roles vary considerably across schools and districts. In this study, I focus on these responsibilities because they are consistent with the survey data and reports from the state on which I am focused.

options as well as the steps to apply to and enroll in college. Students often lack good information about education and career options, so the information counselors provide could improve students' choices (Hastings et. al, 2015; Hoxby & Avery, 2013; Jensen, 2010; Oreopoulos & Dunn, 2013). Counselors may also provide specific recommendations or nudges. Whether this guidance improves or worsens student outcomes likely depends on the guidance provided (Castleman & Goodman, 2018; Hoxby & Turner, 2015; Mulhern, 2020).

4. **Direct Assistance:** Counselors can also directly influence access to educational opportunities. They are often responsible for providing accommodations, enforcing discipline policies, and approving graduation petitions. Counselors are also responsible for obtaining SAT fee waivers and writing letters of recommendation. Both of these actions can influence whether and where students get into college (Hoxby & Turner, 2013; Bulman, 2015; Clinedinst & Koranteng, 2017). In addition, counselors may help students complete applications or forms, which can impact their educational and career trajectories (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).[7]

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 educational attainment without influencing student ability. In this section, I expand the models typically used to show how educators influence educational attainment to incorporate educators' effects on student awareness of long-term options and educators' direct influence on the barriers students face in accessing education and labor market opportunities.

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

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 (similar to teachers in Jackson (2018)). The third channel encompasses counselor effects through information, such as telling students about long-term options, their costs and benefits, and the steps needed to reach them.[8] The fourth channel is direct assistance. 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 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, D_i, to educator effectiveness.[9]

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

The quality of educator j for student i is $\omega_{ji} = D_i \omega_j$. Teacher value-added models (e.g. Jackson, 2018) focus on educators' effects on student ability, modeling student ability as $\alpha_{ij} =$

[8]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.

[9]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.

$\nu_i + \omega_{ij} + \phi_{i-j}$ (where ϕ_{i-j} is the impact of other educators on ability). Some dimensions of counselor effectiveness, however, are unrelated to student ability, so they will not appear important in traditional models of educator effects. I expand on traditional models by adding two dimensions of educator effectiveness and modeling each components' relation 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 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 recommendation letters or enforcement of school discipline and graduation policies. Here, endowments may reflect the assistance students receive from their social networks. The importance of counselor effectiveness, D_{di}, may depend on student characteristics.[10] 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 Y_l, is the sum of her effects on each dimension, weighted by the impor-

[10] 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.

tance of each dimension for Y_l. Formally, the average effectiveness of counselor j on Y_l is

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

Previous studies assume educator effects on Y_l are only through the ability dimension ($\beta_l \alpha_{ij}$), meaning that educators either have no effects on the other dimensions, or those dimensions are irrelevant to Y_l. Formally, they assume $E[\omega_{kij}]\Gamma_l = 0$ 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 direct assistance ψ_{ij}. If $E[\omega_{kij}]\Gamma_l \neq 0$ or $E[\omega_{dij}]\delta_l \neq 0$, then educators impact long-run outcomes through channels other than student ability.

In section 5.2.2 I show evidence that counselors explain meaningful variation in educational attainment 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 by doing more than just impacting students' skills. They can also influence long-term outcomes by providing information and modifying barriers to education or career opportunities. 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 on student demographics, courses, attendance, discipline and standardized tests. The data are linked to National Student Clearinghouse records on postsecondary enrollment and degree completion for students projected to graduate high school from 2008 to 2017. My sample consists of 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 so that parents and students can easily find and contact their counselor. In Massachusetts, at least a third of public high schools assign students to counselors based on the beginning letters of student last names, and many schools posted assignments on their websites in at least a few years between 2004 and 2018. National survey data indicate that over 50% of schools assign counselors based on student last names (High School Longitudinal Study, 2009).[11]

I reviewed the archives of school counseling websites for all Massachusetts high schools between 2004 and 2019 to determine which schools used last name assignment rules in which years. When available, I collected assignment rules from the websites and used them to determine each student's assigned counselor based on his or her last name. Schools adjust assignment rules 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.[12] In most schools, students are assigned the same counselor for 9th-12th grades.[13]

Among Massachusetts' 393 public high schools, I identified 143 which used a last name assignment rule for at least one cohort between 2008 and 2017. 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.[14] 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 all high schools in the state. Suburban high schools are slightly over-represented and urban schools are under-represented. This is largely because very few Boston schools posted last name assignment rules.[15] The schools in my sample tend to be whiter and have fewer low-income students than the state, but lower per-pupil spending than average. My sample includes a few charter and vocational schools.

On average, I observe assignments for 5 cohorts per school in my sample. Many schools are missing website archives for a few years so assignments cannot be verified in every year. For this reason, I impute some assignments and focus on the first counselor linked to each student.[16] In-

[11]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.

[12]On average, the starting letter of a counselor's assignments shifts by less than three letters over the years I observe; 52% of counselors do not change their starting letter and 52% do not change their ending letter.

[13]In a few schools, students on the edge of an assignment rule switch counselors between grades to even caseloads.

[14]An additional 19 schools posted a last name assignment rule in 2018 or 2019. 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. Random assignment policies are rarely posted on websites.

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

[16]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.

cluding imputed assignments increases each school's average duration in my sample to 7 cohorts.

I link 154,905 students (out of 819,268) to 723 counselors. For 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 per cohort.[17] In section 6, when showing how counselor characteristics relate to student outcomes, I do not require a counselor to serve multiple cohorts to be included. In section 7, when computing the relationship between caseloads and student outcomes, I use all Massachusetts high schoolers at a school with reasonable counselor FTE data.[18] 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 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. Table 2 shows that the average counselor in my sample is matched to 184 students each year and 61 students per grade.[19] 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. In addition, many high schools have separate counselors for students with limited English proficiency or those in career and technical education. This means these students are frequently excluded from

[17]This improves the precision of my estimates and enable me to construct leave-year-out estimates of effectiveness.

[18]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 6 increases my power.

[19]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.

my sample. This sample selection probably leads to underestimates of counselor effects since counselors have larger effects on low-income and low-achieving students.

Most data are available for the full period. Course performance data are only available since 2012. Bachelor's degree completion rates are only for cohorts prior to 2013. 10th grade test scores and college persistence rates are not available for the 2017 cohort.[20]

Massachusetts has no regulations for caseloads or counseling duties. The average high school caseload is 285 students, which is close to the national average. Massachusetts does not require schools to have counselors, though many schools have school adjustment counselors, who 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 which consists of guidelines for providing counseling services. It has been adopted by some schools, but is not required. Counselors are required to have a Master's degree and must pass tests to obtain a license.[21]The state also has a formal evaluation process.

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). 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 a counselor 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]Licenses require 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 literacy and communications test.

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 are assigned 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 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.[22]

The key identifying assumption is that, conditional on the first letter of 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.[23] 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 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

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

[23] 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. 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 access to services in high school.

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 across counselors in their effects on student outcomes. Multiple approaches for estimating this variance have been used in the literature. I follow Kraft (2019) and Jackson (2019) and 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 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 from 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 captures 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 Var(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.

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. Since counselors may impact many outcomes, I also create five indices to measure counselor effects on a few main dimensions. The indices are described below. I construct each index using the weights from principal components analysis and standardize them to have a mean of zero and standard deviation of one in the full population of Massachusetts high schoolers.[24]

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	

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 application assistance. I use these indices to test the model from section 2. The fifth index captures counselors' direct effects on 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.

[24] 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.

Next, I construct estimates which can be used to predict the benefits of a one standard deviation improvement in counselor effectiveness. 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.

The leave-year-out estimates $\hat{\mu}_{j-t}$ are constructed in the same manner as $\hat{\mu}_j$, except students from year t are excluded at each step. For each year and outcome I compute $\hat{\mu}_{j-t}$ and standardize the values.[25] Then, I use the counselors' estimated impacts on the indices or outcomes to test whether the out of sample estimate predicts 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.

4.3 Testing for Sorting

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 also shows that, conditional on all controls except eighth grade achievement, students with higher test scores are not assigned counselors who are better at increasing educational attainment.[26] Table A.3 shows additional placebo tests.

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

[26] 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.

I use a rich set of controls to alleviate concerns about sorting, but such a rich set of controls may not be necessary with quasi-random counselor assignment. In fact, column (2) of Table A.3 indicates that simply controlling for the assignment mechanism, using school, cohort, grade, and first letter of last name fixed effects, is sufficient to capture most differences in eighth grade test scores across counselors. Estimates of counselor effects are about twice as large when I do not include demographic controls, thus, to be conservative I focus on models with a rich set of controls.

One downside to including school fixed effects is that it absorbs all inter-school variation in counselor effectiveness. To examine whether statewide variation in counselor effectiveness is different from within school variation in effectiveness, I also use a model which controls for school-level characteristics rather than school fixed effects. These estimates may be upward biased if my controls do not adequately capture student sorting to schools. Placebo tests (Table A.3), however, indicate that counselor effects which have not been purged of school effects, are not related to eighth grade test scores. These estimates are useful for providing an upper bound on the true variation in counselor effects. The effects which include school effects are a lower bound.

5 Counselor Effectiveness

5.1 Magnitude and Variance of Counselor Effects

Figure 1 and 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 than students with an average counselor. Randomization inference (Table A.4) shows that my estimates are significantly larger than those expected due to chance.

Figure 2 and Panel (C) of Table 3 show that counselors also impact what students do in high school. Assignment to a one standard deviation better counselor (in terms of SAT taking) increases

[27] Figure A.2 shows the distribution of counselor effects.

SAT taking rates by 4.2 percentage points. Counselors also influence AP test taking, but there is no significant variation in their effects on GPAs, 10th grade test scores, or attendance. In addition, 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 an average counselor. Thus, counselor assignment can be an important determinant of students' high school experiences.

Panel (B) of Figure 2 and Panel (D) of Table 3 show that counselors influence where students attend college. Counselors vary in their effects on selective college attendance, the graduation rate at the college a student attends, and majoring in a STEM field. Counselors who are one standard deviation above average also direct students to colleges where students' average earnings are $445 higher (from Chetty et al, 2017). Counselor effects on where students attend college may influence college completion and future earnings (Cohodes & Goodman, 2014; Hoekstra, 2008).

Estimates which use across school variation are much larger than those purged of school effects. Column (4) of Table 3 indicates that the upper bound of statewide variation in counselor effects on high school graduation is about 3 percentage points. It is about 4 percentage points for college attendance and 5.5 percentage points for four-year college attendance.

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.5).[28] The appendix contains more details on the variance estimates and their components (Tables A.6 and A.7). In addition, covariance based estimates of the variance are in Table A.8.

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

[28] These estimates come from variation in the duration of counselor assignments. 9th grade counselors may be different from 12th grade ones if counselors leave while a student is in school or if the school hires an additional counselor.

time and is a valid out of sample predictor. Panels (A) and (C) of Figure 3 show that a counselor's predicted effectiveness, in terms of high school graduation or four-year college attendance, is predictive of the relevant outcome. Panel (A) 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 2.2 percentage points. A similar effect is apparent for high school graduation and any college attendance. The 95% confidence intervals of the predicted effect for high school graduation and college attendance contain one (Table A.9).

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 3 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 (B) of Table 4 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 2.1 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.7).

Counselor effects are largest for low-achieving and low-income students.[29] Figure 4 shows the effect of a one standard deviation improvement in counselor effectiveness, in terms of the composite index, on educational attainment for low vs. high-achieving students (in panel (A)) and low vs. high-income students in panel (B). For nearly every measure of educational attainment, counselor effectiveness is more important for low-achieving and low-income students than their peers. A one standard deviation increase in effectiveness leads to a 3 percentage point increase in

[29]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. Low-income is defined as students who received free or reduced=price lunch in eighth grade.

high school graduation for low-income and low-achieving students, while it has nearly no effect on high school graduation for higher income and high-achieving students.

Table 5 indicates that the only outcome on which counselors have similar effects for students of different achievement and income 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 or high-income student attends than the decision of whether to attend college.

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). Among low-income students, counselors are most important for the low-achievers (Table A.10). These results indicate that counselors may be an important resource for closing socioeconomic gaps in education.

Table 5 also shows differences for non-white and white students. These are not significant at the 5% level, but, 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. I find only small differences in counselor effects across males and females (Table A.10) and none of these are significant at the 5% level. This contrasts the large gender differences found by Carrell & Sacerdote (2017) in student responsiveness to peer college mentoring. Counselors also 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. Their effects on four-year college attendance and college graduation rates are largest for middle-achieving students.

My results are similar when I using the methods in Kane and Staiger (2008) or Chetty, Friedman & Rockoff (2014). Results based on these approaches, as well as from a logit specification, are in Table A.11. Table A.12 contains estimates which include school effects.

5.2.2 Channels of Counselor Effects

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

Panel (E) of Table 3 reports the variation in counselor effects on these indices. There is significant variation in counselor effects on all indices, but it is smaller for the cognitive skills index than the other indices. This is consistent with counselors' small effects on GPAs and test scores.

Figure 5 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. Panel (C) of Table 4 shows that for most outcomes, effectiveness in terms of cognitive and non-cognitive skills are not significantly related to educational attainment.[30]

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 short-term cognitive and non-cognitive skill development. Counselor effects on cognitive and non-cognitive skills are unrelated to their effects on educational attainment.[31] Counselors do, however, impact 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.[32] 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.

[30]In a few instances, a counselor's effect on cognitive skills is negatively related to educational attainment. This may just be due to noise since the standard deviation of counselor effects on cognitive skills is quite small.

[31]This is also true when I regress student outcomes on the indices one at a time in Table 6.

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

5.3 Dimensions of Effectiveness

In general, good counselors tend to improve all outcomes. Most measures of effectiveness are positively and highly correlated (Table A.13). Since there is mechanical correlation between value-added measures based on the same students, I use the leave-year-out measures of effectiveness to explore dimensions of effectiveness. Formally, I regress student outcomes from year t on the leave-year-out empirical Bayes estimates ($\bar{\mu}_{j-t}$) of counselor effects on various indices and outcomes.

Table 6 shows how counselors' predicted effectiveness on various dimensions are related to student outcomes. In panel (A), column (5) indicates that a one standard deviation improvement in a counselor's predicted effectiveness on the college readiness index is associated with a 2.2 percentage point increase in a student's probability of graduating high school. This means that counselors who improve college readiness also tend to improve high school graduation. This is consistent with panel (A) of Figure 6 which shows that, on average, students are more likely to attend a four-year college if their counselor is good at improving high school graduation.

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. Figure 6 also indicates that some counselors who are good at increasing one type of educational attainment are not good at the other. Table 6 reports 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 (2.2 percentage points), so effectiveness does not perfectly translate across dimensions.

Most estimates in Table 6 are positive, indicating that most counselors who are good on one dimension are also good on other dimensions. I do not find much evidence of specialization, where counselors focus only on certain outcomes or students at the expense of others. Formal tests of specialization, described in Appendix B, also indicate little specialization.

The main exception is that effectiveness in terms of cognitive skills is not significantly related to effectiveness on other dimensions. In addition, counselors who improve non-cognitive skills tend to be different from those who increase selective college attendance. Panel (B) of Figure 6 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. Improving selective college attendance and student behavior likely require very different skill sets, and apply to different types of students, so it makes sense that more specialization is apparent over these outcomes.

6 Predictors of Counselor Effectiveness

In this section, I use the quasi-random assignment of counselors to measure how assignment 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}).[33]

$$Y_i = \alpha_0 + \alpha_1 CounselorType_j + \beta X_{ij} + \nu_n + \delta_s + \gamma_g + \psi_t + \epsilon_{iy} \tag{10}$$

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.

6.1 Demographics

Table 7 indicates that students are about two percentage points more likely to graduate high school and attend college if assigned a counselor from the same racial group than if assigned a counselor

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

from a different race.[34] These effects are largest for non-white students, who are 4.2 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 have a better understanding of students' experiences and needs. For instance, minority counselors may know more about the unique college access hurdles that minority students face 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 being matched to a counselor of the same gender (Table A.14). If anything, there may be a negative effect, particularly for males (Table A.14).

6.2 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.[35] 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 7 shows that the location of the counselor's undergraduate college is a predictor of counselor effectiveness. Students assigned to counselors who received their bachelor's degree in Massachusetts are 1.8 percentage points more likely to graduate high school than those assigned to

[34]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.

[35]Education data are self-reported. Table 2 compares these counselors to others in terms of experience and demographics. On average, they look similar to the full sample.

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 understanding of the local college options, the needs of local students, or state graduation requirements than counselors educated elsewhere.[36] 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.[37]

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.

6.3 Experience

Most measures of counselor experience are not positively related to student outcomes. Counselors with teaching licenses and supervisors have students with lower educational attainment than other counselors (Table A.14). 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, or because of who is promoted to 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.

[36]Counselors educated in Massachusetts may also more likely to have attended high school in Massachusetts.

[37] 77% of students have a counselor with a master's degree from Massachusetts vs. 59% for a bachelor's degree.

In addition, 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.

Panel (C) of Table 7 indicates that the returns to experience are not positive, and Figure A.3 shows that these estimates are quite noisy. Novice counselors and more experienced counselors are similarly effective. 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 have received more training on the state's current counseling standards or they may be more familiar with technological innovations in the college application process and teen culture that make it easier for them to relate to students.

7 Comparing Counselor Effectiveness to Other Education Inputs

The evidence in the previous sections indicate that high school counselors have significant impacts on educational attainment. From a policy perspective, it is important to understand how important counselor effectiveness is relative to other education inputs given limited school resources. 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.

7.1 Caseloads

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 8 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.[38] 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.[39]

First, I control for student characteristics and school fixed effects. Panels (B) and (C) of Table 8 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 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 8 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

[38] 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.

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

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 8 suggest that, on average, hiring a new counselor would increase high school graduation and four-year college attendance by 0.6 to 0.8 percentage points. The last row of Table 8 indicates that the benefits may be much larger for low-achieving students.

Fourth, I use within school variation in the number of counselors over time. This approach indicates 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 8 indicates no significant relationships associated with changes in the number of counselors in a school.

Finally, I do an event study around when schools hire or lose counselors. Event study plots (Figure A.4) 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.[40] 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 caseload 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.

7.2 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 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 Jackson's (2018) estimates based on 9th grade teachers. These estimates incorporate teacher effects on long-run outcomes through non-

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

cognitive channels, in addition to the test score channel.[41] 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 may impact many more students than improving the effectiveness of one teacher because counselors serve many students.

7.3 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 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 close to the effects of 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

[41] They are also based on some of the same students as the Wake County, NC counselor estimates in section 8.

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. For example, counselors influence how students use and respond to college admissions guidance on Naviance (Mulhern, 2020). Thus, combining scalable guidance with the personalized assistance provided by school counselors may be a way to effectively reach many students.

8 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.16 shows the variance in student outcomes due to counselors.[42] In Wake County, the standard deviation of counselor effects on high school graduation is 0.6 percentage points and it is 1 percentage point for four-year college enrollment. These estimates are all smaller and noisier than those from Massachusetts. This is in part because the Wake County sample is much smaller. Despite being smaller, they still indicate thst counselors explain meaningful variation in

[42] 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.

educational attainment.[43]

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.5 shows that counselors' evaluation scores are not predictive of student outcomes. In fact, the correlation coefficients in Table A.17 are all negative.[44] Scatterplots in Figure A.6 also indicate little relation between a counselor's average evaluation score and her students' high school graduation and four-year college attendance rates.[45]

These correlations indicate that evaluations pick up on a different set of skills than the effects I measure. The items on the evaluation rubric are most focused on how counselors support students within the school, promote diversity, demonstrate leadership, and implement 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.

9 Conclusion

This paper shows that high school counselors have large impacts on their students' human capital accumulation and educational attainment. Counselors significantly vary in their effectiveness

[43]The Wake county results are also more sensitive to controls. Using more limited controls substantially increases the estimated variance of counselors effects. This may be because the Wake County sample is much smaller and the controls absorb more variation here than in Massachusetts. For example, fitting models without the counselor by cohort parameter increases estimates of the standard deviation of counselor effects on high school graduation and four-year college attendance to two percentage points.

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

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

and are an important element of the education production function.[46] 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 and closing socioeconomic gaps in education.

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

[46] A one standard deviation improvement in counselor effectiveness is associated with about a third of the increase in high school graduation rates that result from a 10% increase in school spending from Kindergarten through 12th grade (Jackson, Johnson & Persico, 2015).

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 assignment to counselors from the same racial group. Counselor effectiveness also matters most for low-income and low-achieving students, so there could be benefits from matching the best counselors to these students. There may, however, be negative consequences from purposeful matching 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 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 economic choices and outcomes of the individuals they serve.

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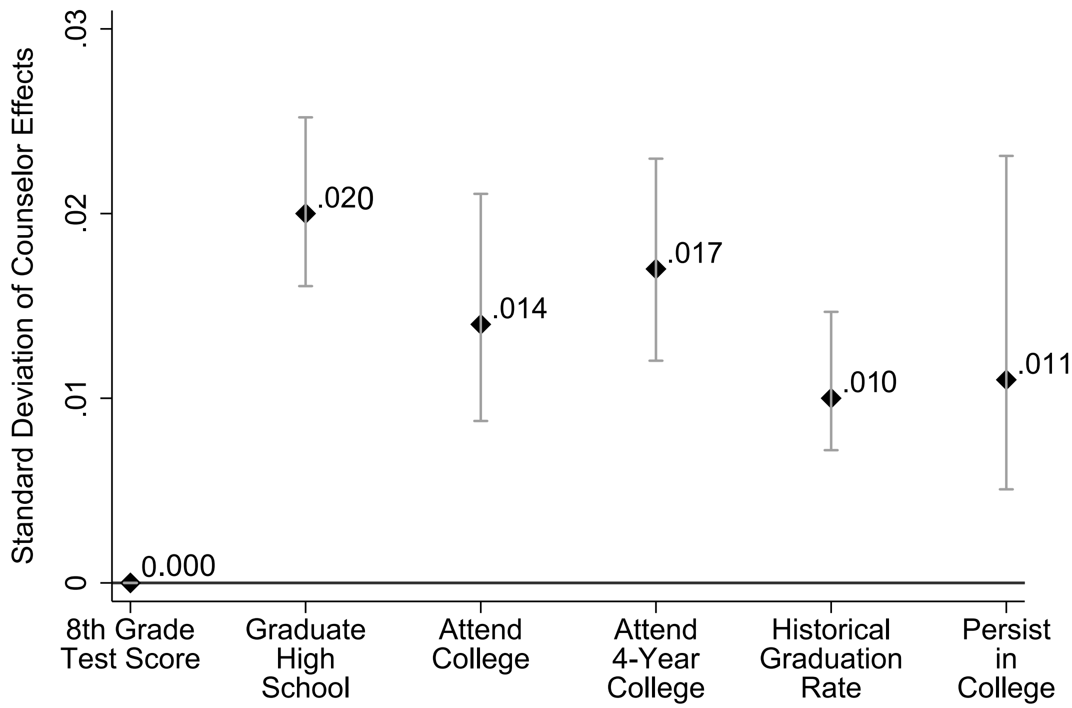
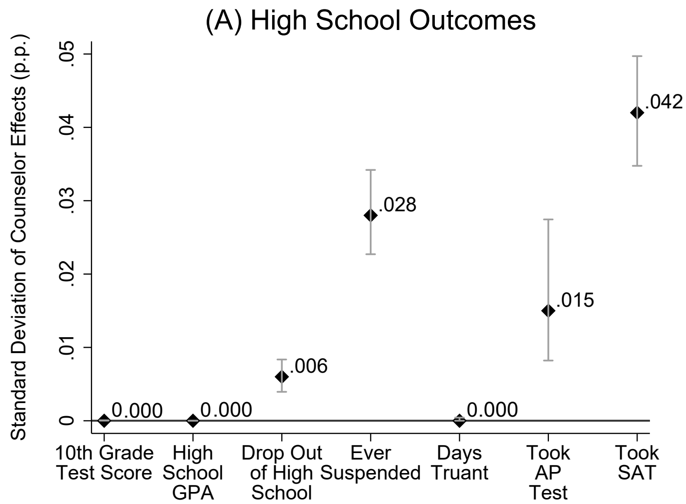
11 Figures and Tables

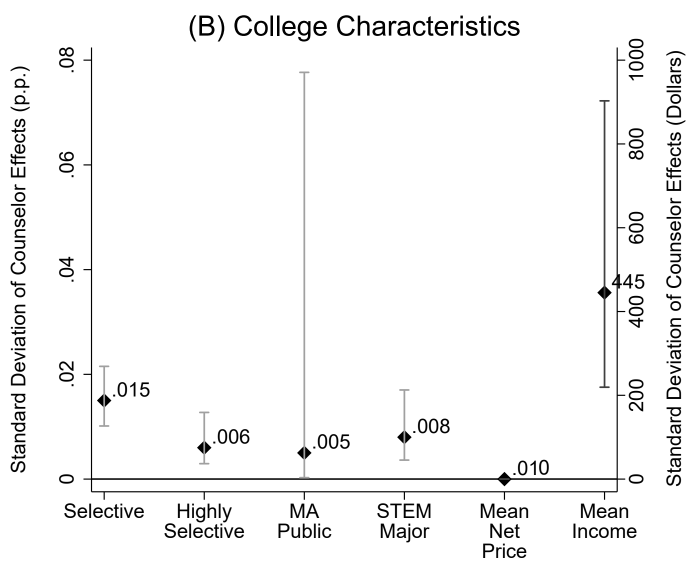
Figure 1: Standard Deviations of Counselor Effects on Educational Attainment



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.

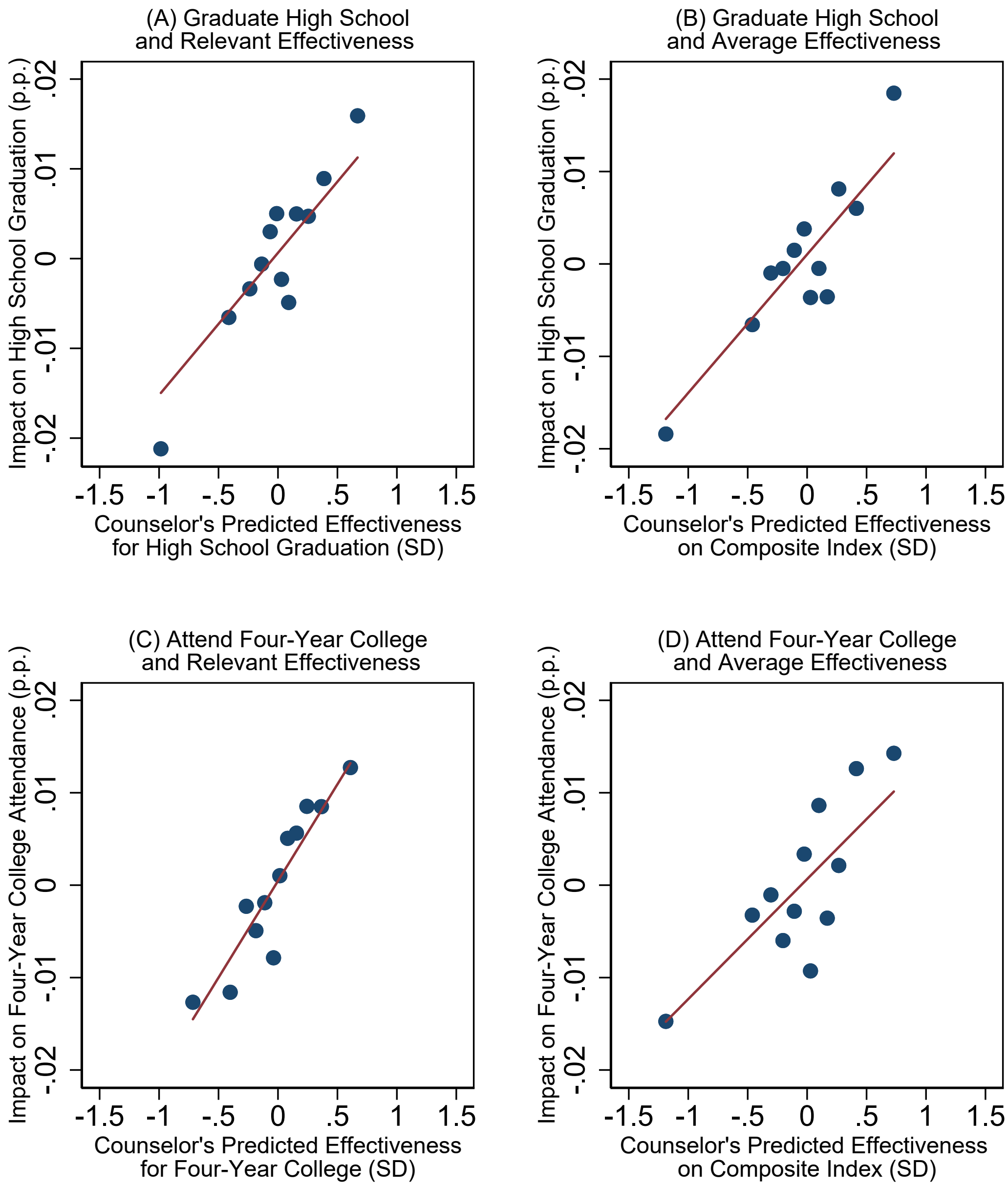
Figure 2: Standard Deviations of Counselor Effects on Additional Outcomes





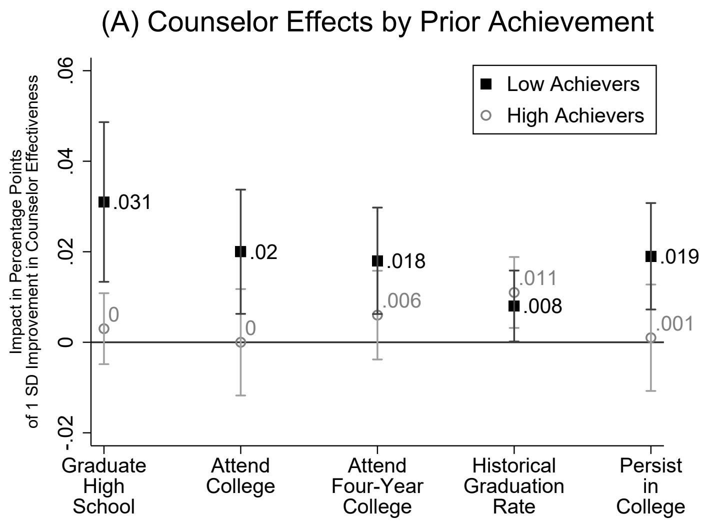
Notes: The figures above indicate the standard deviations of counselor effects. The 95% confidence intervals of the standard deviations are represented by the error bars. The estimates indicate the standard deviation of counselors' effects on various outcomes in high school and the types of colleges that students attend. All estimates are in percentage points except for 10th grade test scores (in standard deviations) and mean net price and mean income, which are in dollars. 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. Days truant means the number of unexcused absences a student has. Suspended refers to whether a student was ever suspended. The college characteristics in panel (B) are zero for students who do not attend college, except mean net price is missing for those who do not attend and mean income is the average income of students who didn't attend college. Counselor effects on college selectivity and stem majors are larger when only looking at college attendees.

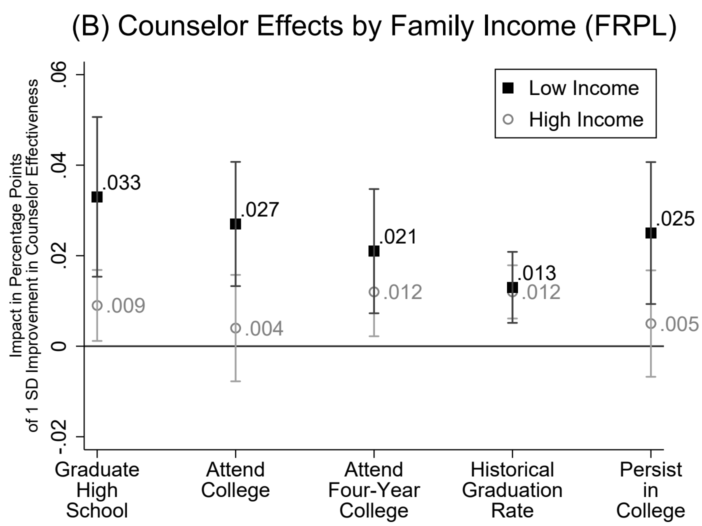
Figure 3: Impacts by Counselors' Predicted Effectiveness



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.

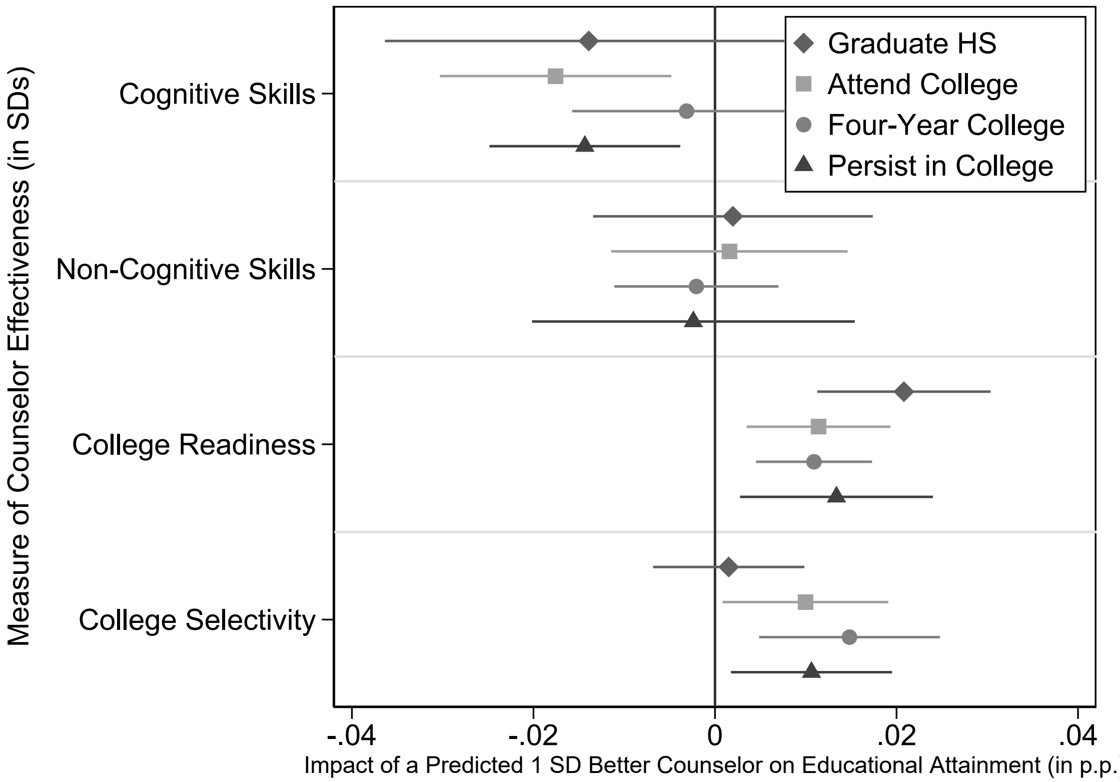
Figure 4: Importance of Counselor Effectiveness by Student Type





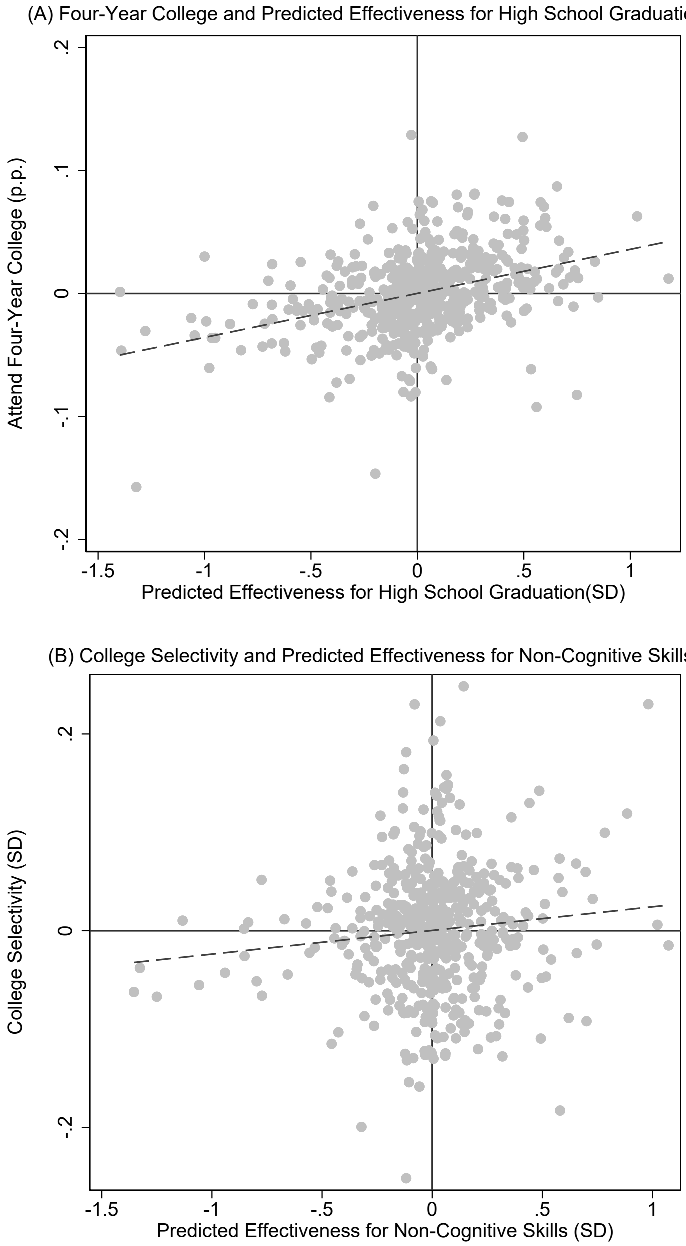
Notes: The figures above show the relationship between a counselor's predicted effectiveness on the composite index and measures of educational attainment, separately by student type. Panel (A) divides students by whether they are above or below average on the 8th grade tests. Low-achieving students are those with eighth grade test scores below the state average and high achievers are those with above average eighth grade test scores. The coefficients indicate the benefit of assignment to a counselor who is one standard deviation above average relative to an average counselor (as measured by the composite index and students in other years). The composite index of effectiveness incorporates effects on educational attainment, cognitive and non-cognitive skills, college readiness and college selectivity. Panel (B) divides students by whether they received free or reduced-price lunch in eighth grade. Low-income students are defined as those who received free or reduced-price lunch in eighth grade and high income students are those who did not receive it (though they are not necessarily from high income families.) The error bars represent 95% confidence intervals. These estimates are from models which include 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. Standard errors are clustered by counselor and cohort. 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 5: Relationship Between Short-Term Effects and Educational Attainment



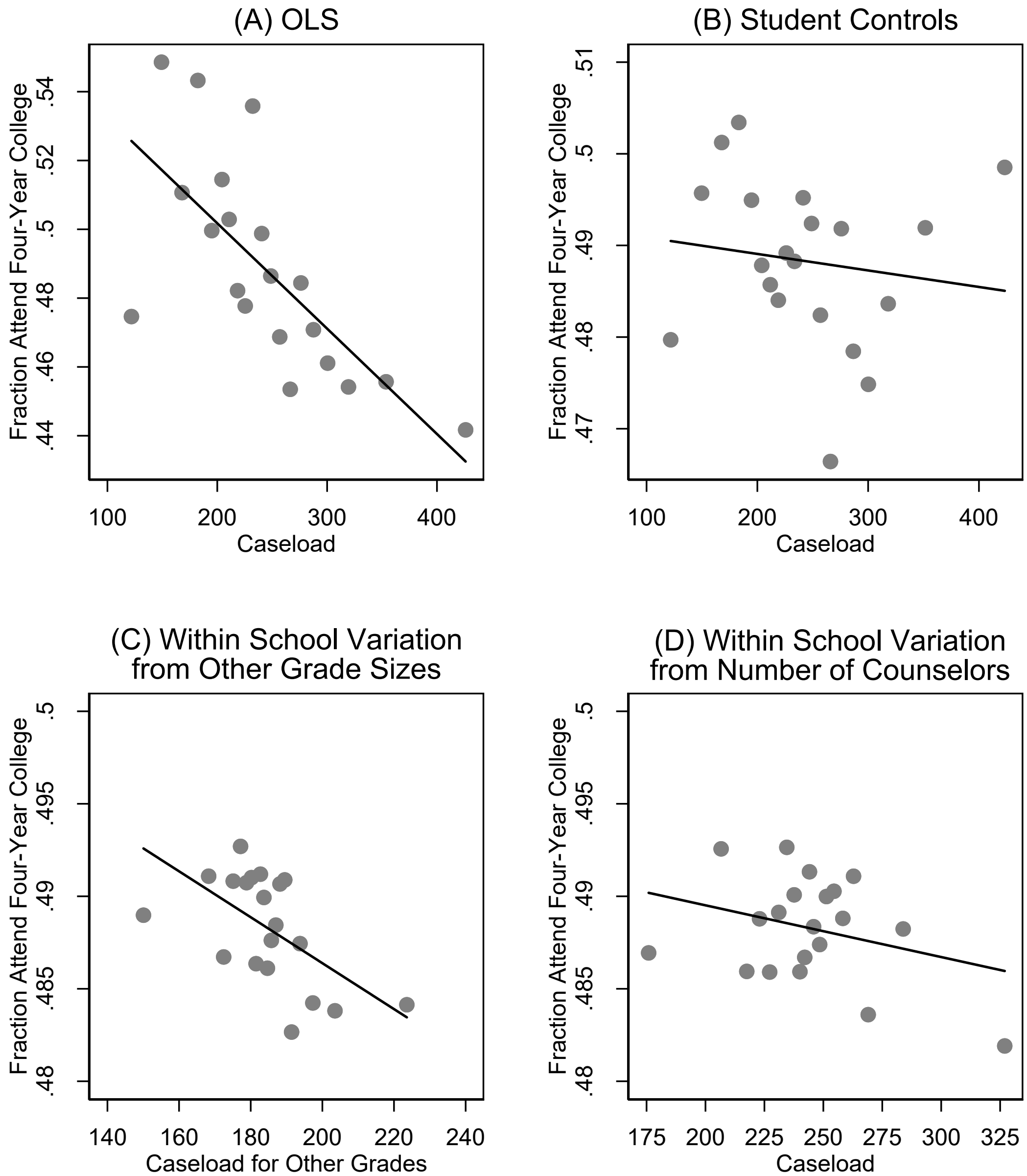
Notes: This figure shows the relationship between counselors' predicted effectiveness on four short-term dimensions of effectiveness (cognitive skills, non-cognitive skills, college readiness and college selectivity) and students' educational attainment. The estimates are from regressions of the outcome variable on all four measures of effectiveness in addition to controls for student demographics, eighth grade achievement, eighth grade attendance and services received, plus 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. Standard errors are clustered by counselor and cohort.

Figure 6: Dimensions 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 7: Counselor 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 Massachusetts 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. It is zero for students who did not attend 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				
Doctorate	0.02	0.03	0.03	0.02
Supervisor	0.09	0.12	0.12	0.06
Teaching License	0.13	0.08	0.08	0.11
Years Experience	2.72	4.38	4.38	2.72
Switch Schools	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. Teaching License indicates whether the counselor has an active teaching license in Massachusetts. 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 schools indicates the fraction of counselors who switched schools within Massachusetts.

Table 3: Standard Deviations of Counselor Effects

	School Effects Purged			With School Effects				
	Standard Deviation (1)	Standard Error of SD (2)	Percent Change (3)	Standard Deviation (4)	Standard Error of SD (5)	Percent Change (6)	Mean (7)	N Students (8)
(A) Placebo Test								
8th Grade Test	0.000	(0.000)	0%	0.000	(0.000)	0%	0.15	142,161
Math Test	0.000	(0.000)	0%	0.000	(0.000)	0%	0.15	142,161
Reading Test	0.000	(0.000)	0%	0.000	(0.000)	0%	0.15	142,161
(B) Educational Attainment								
Graduate High School	0.020***	(0.002)	2%	0.028***	(0.002)	3%	0.87	142,161
Attend College	0.014***	(0.003)	2%	0.036***	(0.002)	5%	0.67	142,161
Attend Four-Year	0.017***	(0.003)	3%	0.055***	(0.002)	10%	0.54	142,161
Persist 1st Year	0.011***	(0.004)	2%	0.036***	(0.002)	6%	0.57	121,041
(C) High School Outcomes								
Ever Suspended	0.028***	(0.003)	22%	0.041***	(0.002)	32%	0.13	142,161
10th Grade Test	0.000	(0.000)	0%	0.101***	(0.005)		0.17	121,634
HS GPA	0.000	(0.000)	0%	0.112***	(0.005)	4%	2.79	121,314
Log Absences	0.000	(0.000)	0%	0.137***	(0.006)	4%	3.34	142,161
Took AP Test	0.015***	(0.005)	4%	0.092***	(0.004)	25%	0.37	142,161
Took SAT	0.042***	(0.004)	6%	0.060***	(0.003)	9%	0.67	142,161
Max SAT	33***	(5.4)	2%	64***	(4.2)	4%	1531	142,161
(D) College Type								
Selective College	0.015***	(0.003)	4%	0.050***	(0.002)	13%	0.39	142,161
Historical Grad Rate	0.010***	(0.002)	3%	0.047***	(0.002)	14%	0.38	142,161
Average Net Price	0.0	(0.0)	0%	909	(37)	7%	13,243	142,161
Mean Student Income	445***	(161)	1%	3028 ***	(119)	7%	42,323	142,161
STEM Major	0.008***	(0.003)	3%	0.027***	(0.002)	9%	0.30	142,161
(E) Indices								
Composite Index	0.052***	(0.006)		0.106***	(0.005)		0.27	142,161
Cognitive Skills	0.015***	(0.008)		0.090***	(0.004)		0.18	121,045
Non-cognitive Skills	0.045***	(0.006)		0.124***	(0.006)		0.11	142,161
College Readiness	0.080***	(0.008)		0.131***	(0.007)		0.24	142,161
College Selectivity	0.029***	(0.006)		0.153***	(0.006)		0.23	142,161
Education	0.041***	(0.005)		0.082***	(0.005)		0.27	142,161

Notes: (*p<.10 **p<.05 *** p<.01). The estimates in columns (1) and (4) 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 columns (2) and (5). 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, grade, and cohort, as well as random effect parameters for counselor by cohort shocks. Estimates in columns (2) -(4) also include school fixed effects, thus purging variation in counselors across schools. Columns (5) - (7) include school level means of student characteristics rather than fixed effects, so they include across school variation in counselor effectiveness. 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. It is zero for students who do not attend college.

Table 4: 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)	Composite Index (6)
(A) Relevant Outcome						
Effectiveness (SD)	0.019***	0.015**	0.022***	0.015***	0.007	0.076***
	(0.005)	(0.005)	(0.005)	(0.003)	(0.010)	(0.017)
(B) Overall Effects						
Composite Index	0.021***	0.015**	0.017***	0.013***	0.015**	0.076***
	(0.005)	(0.005)	(0.005)	(0.003)	(0.005)	(0.017)
(C) Indices of Effectiveness						
Cognitive Skills	-0.014	-0.018**	-0.003	0.001	-0.014**	-0.017
	(0.010)	(0.006)	(0.006)	(0.003)	(0.005)	(0.012)
Non-Cognitive Skills	0.002	0.002	-0.002	-0.002	-0.002	0.025
	(0.007)	(0.006)	(0.004)	(0.003)	(0.008)	(0.016)
College Readiness	0.021***	0.011***	0.011***	0.010***	0.013**	0.066***
	(0.004)	(0.004)	(0.003)	(0.002)	(0.005)	(0.009)
College Selectivity	0.002	0.010**	0.015***	0.008*	0.011**	-0.002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.009)
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 cohort. 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 composite 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 5: 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)	Composite Index (6)
(A) By Prior Achievement						
Low Achievers	0.031***	0.020**	0.018**	0.008*	0.019***	0.110***
	(0.009)	(0.007)	(0.006)	(0.004)	(0.006)	(0.030)
High Achievers	0.003	-0.000	0.006	0.011**	0.001	0.033***
	(0.004)	(0.006)	(0.005)	(0.004)	(0.006)	(0.010)
P-value Diff	0.01	0.04	0.09	0.60	0.02	0.02
Low Achiever Mean	0.81	0.47	0.26	0.16	0.36	-0.44
High Achiever Mean	0.95	0.81	0.73	0.53	0.73	0.73
(B) By Income						
Low Income	0.033***	0.027***	0.021**	0.013***	0.025**	0.110***
	(0.009)	(0.007)	(0.007)	(0.004)	(0.008)	(0.027)
High Income	0.009*	0.004	0.012**	0.012***	0.005	0.043***
	(0.004)	(0.006)	(0.005)	(0.003)	(0.006)	(0.013)
P-value Diff	0.02	0.03	0.30	0.88	0.09	0.02
Low Income Mean	0.76	0.45	0.27	0.17	0.33	-0.39
High Income Mean	0.92	0.76	0.66	0.47	0.67	0.55
(C) By Race						
Non-White	0.031**	0.021**	0.012	0.008	0.017**	0.097***
	(0.010)	(0.008)	(0.007)	(0.004)	(0.007)	(0.026)
White	0.015***	0.012**	0.019***	0.015***	0.013**	0.061***
	(0.004)	(0.004)	(0.004)	(0.003)	(0.005)	(0.013)
P-value Diff	0.09	0.19	0.26	0.15	0.50	0.05
Non-white Mean	0.78	0.54	0.37	0.26	0.43	-0.12
White Mean	0.89	0.70	0.58	0.41	0.61	0.36

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 cohort. 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 6: Dimensions of Counselor Effectiveness

	Student Outcomes							
	Indices (SD)							
	Cognitive Skills (1)	Non-Cognitive Skills (2)	College Readiness (3)	College Selectivity (4)	Graduate High School (5)	Four-Year College (6)	Attend Highly Selective (7)	Persist 1st Year (8)
(A) Indices of Effectiveness								
Cognitive Skills	0.018	-0.023	-0.008	0.006	-0.010	0.003	-0.009	0.004*
	(0.019)	(0.043)	(0.032)	(0.009)	(0.013)	(0.006)	(0.006)	(0.002)
Non-Cognitive Skills	0.051	0.108***	0.089**	0.011	0.016**	0.007	0.008	-0.001
	(0.051)	(0.026)	(0.027)	(0.007)	(0.007)	(0.004)	(0.006)	(0.001)
College Readiness	0.048	0.074***	0.114***	0.030***	0.022***	0.013***	0.014***	0.002
	(0.038)	(0.016)	(0.023)	(0.007)	(0.005)	(0.004)	(0.004)	(0.002)
College Selectivity	0.015	0.013	0.045***	0.038***	0.012**	0.020***	0.015***	0.006*
	(0.015)	(0.014)	(0.010)	(0.011)	(0.004)	(0.004)	(0.004)	(0.003)
(B) Outcome Effectiveness								
Graduate High School	0.035	0.044**	0.075***	0.023***	0.019***	0.012**	0.015**	0.002
	(0.027)	(0.016)	(0.014)	(0.005)	(0.005)	(0.004)	(0.005)	(0.001)
Attend Four-Year College	0.019*	0.019	0.039***	0.036***	0.012*	0.022***	0.018***	0.004
	(0.010)	(0.012)	(0.009)	(0.006)	(0.006)	(0.005)	(0.005)	(0.003)
N	142,161	142,161	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 cohort. 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 estimates of counselor effects. College attendance is based on attendance within six months of finishing high school. The estimates in columns (1) - (4) are in standard deviations. Those in columns (5) - (8) are in percentage points. All rows are from separate models, so that the effects of each effectiveness measure are separately estimated.

Table 7: Impact of First Counselor's Characteristics

	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	0.020***	0.025***	0.017***	0.008	0.014	0.037***
	(0.007)	(0.008)	(0.006)	(0.005)	(0.010)	(0.014)
Non-White Match	0.042***	0.043***	0.038***	0.015	0.035*	0.085***
	(0.015)	(0.014)	(0.009)	(0.009)	(0.019)	(0.028)
White Match	0.008	0.021***	0.007	0.005	0.010	0.011
	(0.005)	(0.007)	(0.008)	(0.005)	(0.008)	(0.014)
N	142,161	142,161	142,161	142,161	121,041	142,161
(B) Undergrad College						
In Massachusetts	0.018**	0.014*	0.009	0.008**	0.005	0.027*
	(0.007)	(0.008)	(0.007)	(0.004)	(0.010)	(0.015)
Selective	-0.008	-0.001	-0.006	0.001	-0.010	-0.028*
	(0.006)	(0.007)	(0.007)	(0.005)	(0.009)	(0.015)
N	29,007	29,007	29,007	29,007	23,556	29,007
(C) Years Experience (9th Grade)						
Novice	-0.004	-0.006	0.004	0.002	0.001	-0.023**
	(0.006)	(0.006)	(0.006)	(0.004)	(0.006)	(0.011)
Log(Years)	-0.005*	-0.004	-0.004	-0.001	-0.003	-0.007
	(0.003)	(0.004)	(0.004)	(0.002)	(0.005)	(0.009)
N	83,647	83,647	83,647	83,647	70,166	83,647

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. 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). Panel (C) is based on the counselor's years of experience as of a student's 9th grade year. 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 8: Impact of Caseloads

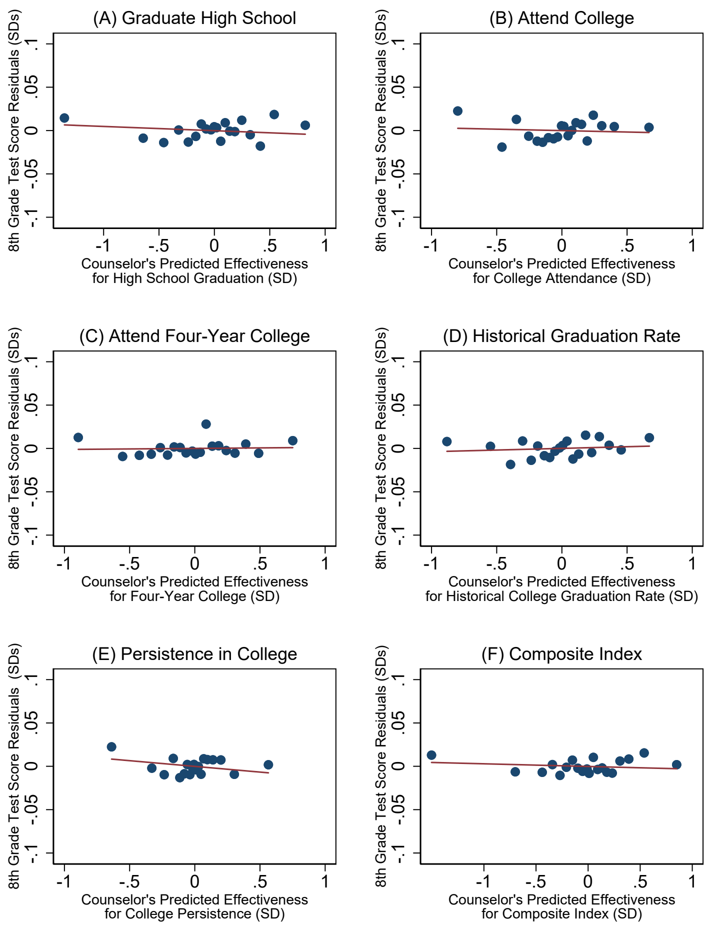
	Grade 9 Caseload	Grade 11 Caseload				
	Graduate High School (1)	Attend College (2)	Attend Four-Year College (3)	Historical Graduation Rate (4)	Persist 1st Year (5)	Composite Index (6)
(A) OLS Caseload						
Caseload (in 100s)	-0.032**	-0.018	-0.031*	-0.039**	-0.020	-0.095**
	(0.012)	(0.011)	(0.015)	(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 Variation Counselors						
Caseload (in 100s)	0.001	-0.002	-0.003	-0.002	-0.003	-0.006
	(0.002)	(0.002)	(0.003)	(0.002)	(0.004)	(0.008)
(E) Within School Variation HS Size						
Caseload (in 100s)	-0.011	-0.009	-0.010	-0.008**	-0.003	-0.018
	(0.007)	(0.007)	(0.005)	(0.003)	(0.007)	(0.015)
(F) Within School Variation Other Grade Size						
Caseload (in 100s)	-0.015	-0.012	-0.012*	-0.010**	-0.004	-0.024
	(0.009)	(0.008)	(0.007)	(0.004)	(0.008)	(0.019)
For High Achievers	-0.014	-0.002	-0.000	-0.011	0.000	-0.019
	(0.009)	(0.008)	(0.011)	(0.007)	(0.009)	(0.025)
For Low Achievers	-0.014	-0.018*	-0.026**	-0.010	-0.010	-0.027
	(0.009)	(0.008)	(0.009)	(0.007)	(0.009)	(0.021)
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 composite index). College attendance is based on attendance within six months of finishing 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 - For Online Publication

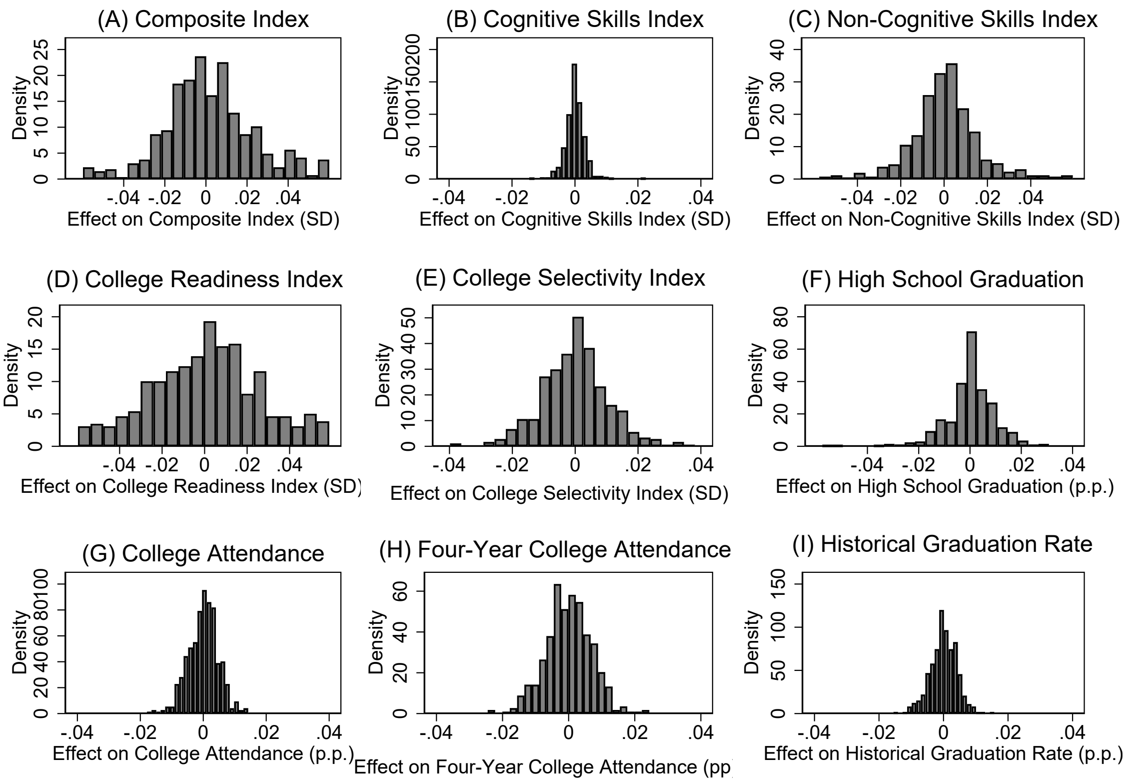
A Additional Figures and Tables

Figure A.1: Placebo Tests



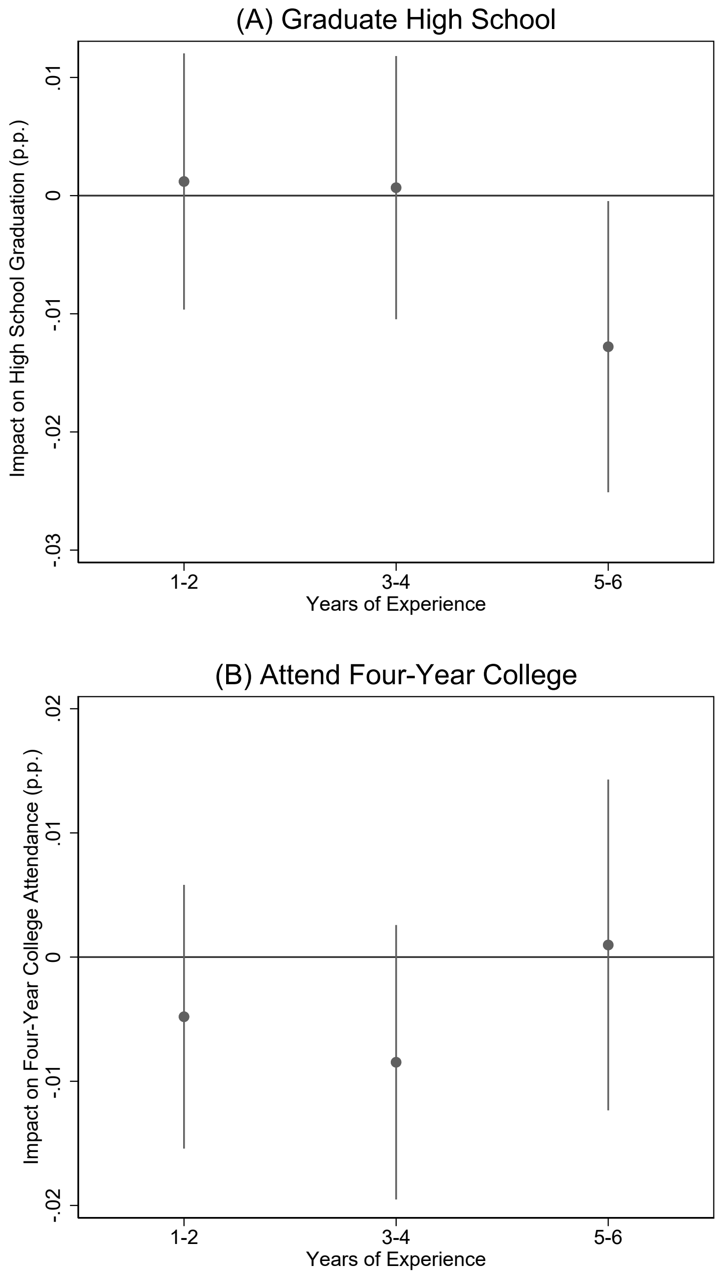
Notes: The figures above show binscatters of counselors' predicted effectiveness and students' eighth grade test scores. The y-axis indicates students' 8th grade test scores (for year t) residualized on the first letter of the student's last name, school, grade, and year fixed effects as well as controls 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, panel (D) for the historical graduation rate at the institution a student attends, panel (E) for persistence between a first and second year of college, and panel (F) for the composite index. 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: Distribution of Counselor Effects



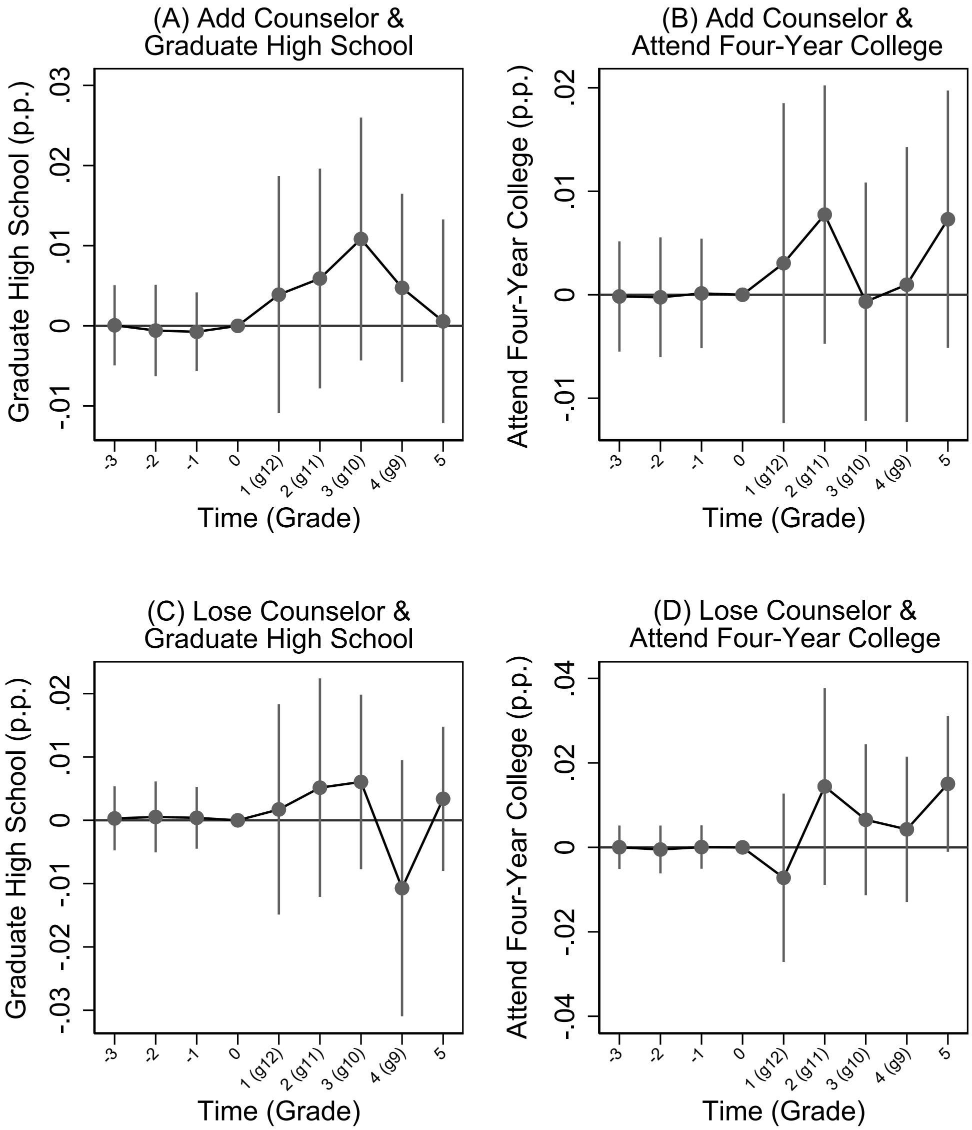
Notes: The figures above show histograms of counselor effects. These are based on empirical Bayes estimates of effectiveness for all students a counselor has served in my sample. Each counselor is represented once. Panels (A) through (E) are in standard deviation units (for the given index). Panels (F) through (I) indicate counselor effects in terms of percentage points on the relevant outcome.

Figure A.3: Impact of Counselor Experience in MA



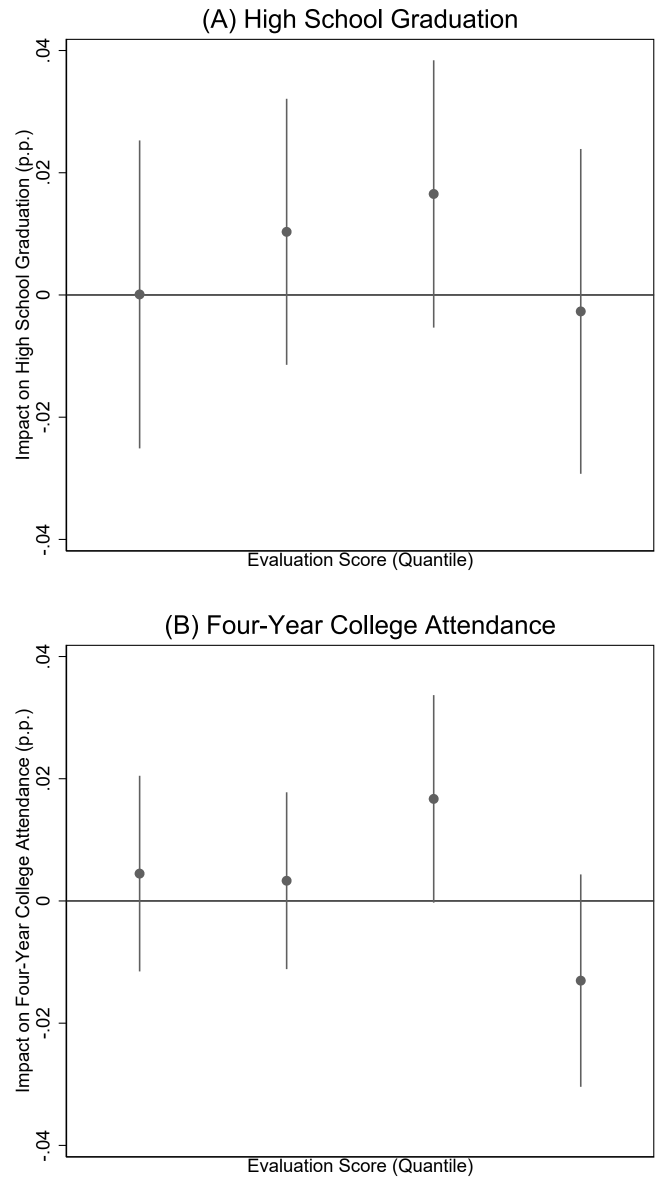
Notes: The figures above show the coefficients from a regression of an indicator for high school graduation (in panel (A)) or four-year college attendance (in panel (B)) on indicators for two-year bins of a counselor's years of experience (in Massachusetts as a counselor). The effects are in percentage points. They are from models which include 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.4: Event Study around Number of Counselors in a School



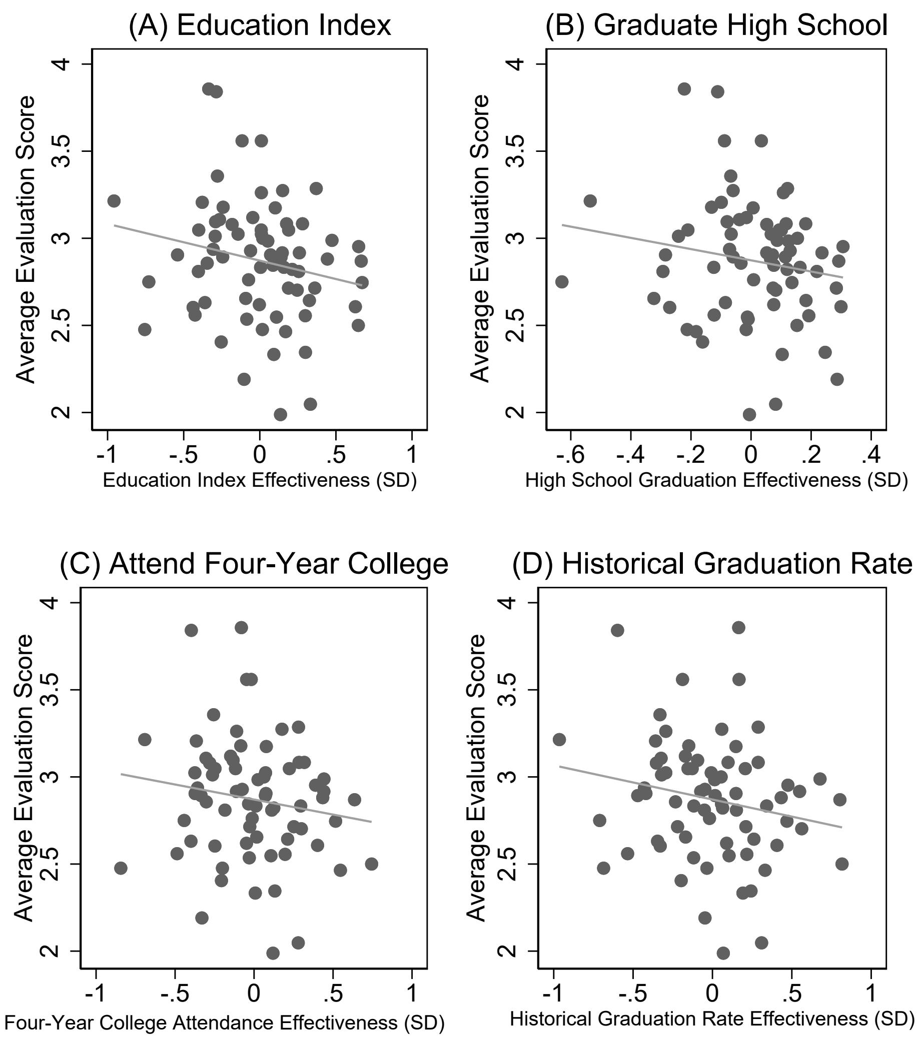
Notes: The figures above show how high school completion (in panels (A) and (C)) or four-year college attendance (in panels (B) and (D)) change when the number of counselors at a school increases (panels (A) and (B)) or decreases (panels (C) and (D)). Time 1 on the x-axis is when 12th graders first received 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.5: 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, North Carolina. 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.6: 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. Effectiveness is in standard deviations. 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

	School Effects Purged		With School Effects	
	(1)	(2)	(3)	(4)
(A) Outcome Based Effectiveness				
Graduate High School	-0.006	0.007	-0.002	0.001
	(0.013)	(0.013)	(0.008)	(0.008)
Attend College	-0.004	0.017	0.002	0.001
	(0.013)	(0.017)	(0.005)	(0.004)
Four-Year College Attendance	0.001	0.023	0.001	0.000
	(0.008)	(0.019)	(0.004)	(0.002)
Historical Graduation Rate	0.004	0.038	0.002	0.001
	(0.010)	(0.024)	(0.003)	(0.002)
Persist 1st Yr Persistence	-0.014	0.007	-0.000	-0.002
	(0.018)	(0.023)	(0.005)	(0.004)
(B) Indices of Effectiveness				
Composite Index	-0.004	0.009	0.002	-0.001
	(0.013)	(0.018)	(0.005)	(0.005)
Cognitive	0.002	0.015	0.002	-0.002
	(0.013)	(0.049)	(0.003)	(0.001)
Non-Cognitive Skills	-0.015	-0.045	-0.004	-0.003
	(0.015)	(0.045)	(0.006)	(0.003)
College Readiness	-0.003	0.011	0.002	0.001
	(0.012)	(0.017)	(0.005)	(0.004)
College Selectivity	0.006	0.048^{*}	0.002	0.000
	(0.009)	(0.026)	(0.002)	(0.001)
Education Index	-0.002	0.016	0.001	0.002
	(0.011)	(0.013)	(0.005)	(0.006)
N	142,161	142,161	142,161	142,161
Demographic Controls	X		X	

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, grade, and cohort. Estimates are based on the first counselor to which a student is quasi-randomly assigned. All columns include controls for whether the student took an 8th grade test. Estimates in columns (1) and (3) contain controls for 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 columns (1) and (2) include school fixed effects. Estimates in columns (3) and (4) include controls for the school level means of student characteristics. 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: Randomization-Based Inference on Variance Estimates

	Graduate HS (1)	Attend College (2)	Attend Four-Year (3)	Historical Grad Rate (4)	Persist 1st Year (5)	Composite Index (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	0.005	0.005	0.005	0.002	0.015
Std. Dev (of SD)	0.0022	0.0041	0.0041	0.0025	0.0034	0.0071
Min	0.000	0.000	0.000	0.000	0.000	0.000
Max	0.013	0.013	0.016	0.010	0.013	0.028
95th Percentile	0.012	0.011	0.011	0.009	0.010	0.026
99th Percentile	0.013	0.012	0.013	0.009	0.012	0.028
P-value	0.000	0.000	0.000	0.005	0.045	0.000

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 estimates from randomization inference. This involves randomly re-assigning counselors (within schools and years) and estimating the variance of these placebo counselors' effects. These estimates are based on 200 iterations of random re-assignment. Panel (B) reports the mean standard deviation of counselor effects in these placebo exercises, the standard deviation of these 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.5: Variance in Outcomes due to Counselors by Grade

	Graduate High School (1)	Attend College (2)	Attend Four-Year College (3)	Historical Graduation Rate (4)	Composite Index (5)
(A) Grade 9					
SD	0.020	0.012	0.010	0.003	0.029
	(0.003)	(0.004)	(0.004)	(0.005)	(0.010)
(B) Grade 10					
SD	0.013	0.010	0.009	0.007	0.024
	(0.003)	(0.005)	(0.005)	(0.003)	(0.012)
(C) Grade 11					
SD	0.010	0.000	0.010	0.008	0.028
	(0.003)	(0.000)	(0.004)	(0.003)	(0.009)
(D) Grade 12					
SD	0.013	0.011	0.018	0.011	0.036
	(0.002)	(0.004)	(0.003)	(0.002)	(0.007)

Notes: The SD (standard deviation) is estimated via restricted maximum likelihood from models controlling for students' demographics, eighth grade achievement and services received, 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 student is enrolled. The effects in columns 1-4 are in percentage points. Those in column 5 are in standard deviation units (of the composite 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.6: 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	0.789	0.662
Counselor SD	0.020	0.014	0.017	0.010	0.011	0.041	0.053	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	0.633	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.7: 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)
$\hat{Var}(\mu_{jy})$	0.0028	0.0002	0.0020	0.0063	0.0008	0.0016	0.0004	0.0003
$Var(\bar{\mu}_{jy})$	0.0048	0.0039	0.0064	0.0096	0.0042	0.0043	0.0008	0.0011
ρ_{FE}	0.583	0.051	0.313	0.656	0.190	0.372	0.500	0.273

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.8: Covariance Based Estimates of Variance

	Graduate High School	Attend College	Attend Four-Year College	Historical Graduation Rate	Persist 1st Year	Composite Index
	(1)	(2)	(3)	(4)	(5)	(6)
(A) OLS						
Std Dev	0.021	0.016	0.014	0.008	0.012	0.048
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 roots of the 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 cohort, 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.9: Validity of Predicted Effects

	Graduate High School (1)	Attend College (2)	Attend Four-Year (3)	Historical Graduation Rate (4)	Indices (SD) Education Index (5)	Indices (SD) Composite Index (6)
(A) Purged of School Effects						
Unit Increase VA	0.921***	1.110**	1.351***	1.440***	1.128***	1.444***
	(0.261)	(0.381)	(0.291)	(0.275)	(0.270)	(0.331)
SD Increase VA	0.019***	0.015**	0.022***	0.015***	0.046***	0.076***
	(0.005)	(0.005)	(0.005)	(0.003)	(0.011)	(0.017)
SD of Effects	0.020	0.014	0.017	0.010	0.041	0.053
(B) Including School Effects						
Unit Increase VA	0.872***	1.009***	0.999***	1.003***	0.979***	1.031***
	(0.151)	(0.090)	(0.039)	(0.041)	(0.086)	(0.078)
SD Increase VA	0.024***	0.036***	0.055***	0.047***	0.080***	0.110***
	(0.004)	(0.003)	(0.002)	(0.002)	(0.007)	(0.008)
SD of Effects	0.028	0.036	0.055	0.047	0.082	0.106
N	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, grade and cohort. 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. Estimates in panel (B) include controls for school level means of these variables. The estimates in panel (A) include school fixed effects instead. The effects in columns (1) - (3) are in terms of percentage points. Those in columns (4) - (5) are in standard deviation units. The estimates in row one of each panel indicate the effect of a one unit better counselor based on the leave-year-out estimates of counselor effectiveness. The estimates in row two of each panel 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. College attendance is based on attendance within six months of completing high school.

Table A.10: 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)	Composite Index (6)
(A) Gender						
Male	0.025***	0.014*	0.013**	0.009**	0.010	0.081***
	(0.006)	(0.007)	(0.006)	(0.003)	(0.006)	(0.021)
Female	0.017**	0.016***	0.020***	0.016***	0.019***	0.071***
	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.015)
P-value Diff	0.10	0.72	0.18	0.14	0.21	0.34
(B) Low Income by Achievement						
High Achieving	0.008	0.006	0.009	0.006	0.005	0.040*
	(0.006)	(0.011)	(0.010)	(0.006)	(0.010)	(0.018)
Low Achieving	0.032**	0.014	0.005	0.003	0.008	0.106**
	(0.011)	(0.008)	(0.007)	(0.005)	(0.007)	(0.036)
P-value Diff	0.05	0.45	0.22	0.80	0.16	0.12
(C) Special Education						
Special Ed	0.035***	0.024**	0.011	0.001	0.018**	0.094**
	(0.010)	(0.008)	(0.009)	(0.009)	(0.006)	(0.035)
Not Special Ed	0.018***	0.014**	0.018***	0.015***	0.014**	0.072***
	(0.005)	(0.005)	(0.005)	(0.003)	(0.005)	(0.016)
P-value Diff	0.07	0.20	0.51	0.19	0.60	0.43
(D) Three Levels Prior Achievement						
Low Achieving	0.043**	0.019**	0.014	0.008	0.017*	0.121**
	(0.014)	(0.008)	(0.012)	(0.008)	(0.009)	(0.042)
Medium Achieving	0.013**	0.015**	0.022***	0.015***	0.017**	0.068***
	(0.005)	(0.006)	(0.006)	(0.004)	(0.007)	(0.016)
High Achieving	-0.008	-0.020	-0.027*	-0.005	-0.027	-0.031
	(0.005)	(0.011)	(0.014)	(0.008)	(0.014)	(0.022)
(E) Location						
Rural	0.019**	0.008	0.012	0.011**	0.007	0.079***
	(0.007)	(0.006)	(0.007)	(0.004)	(0.006)	(0.019)
Suburban	0.018***	0.017**	0.023***	0.016***	0.016**	0.074***
	(0.004)	(0.006)	(0.005)	(0.003)	(0.005)	(0.012)
Urban	0.024**	0.018*	0.014*	0.010**	0.019*	0.076**
	(0.011)	(0.009)	(0.007)	(0.004)	(0.009)	(0.026)
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, each school, grade and cohort. 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. In panels (B) and (D) achievement is based on 8th grade test scores. In panel (B) high achieving low-income students are those who received free or reduced-price lunch in 8th grade and were in the top half of the state distribution on their test scores. Low-income low-achieving students received free or reduced-price lunch and were in the bottom half of the 8th grade test distribution. In panel (D), low achieving is defined as students with 8thg grade test scores more than 1 SD below average, medium achieving is those whose scores are within 1 SD of average, and high achieving students have test scores more than 1 SD above average. In panel (C) special education is defined based on 8th grade status.

Table A.11: Alternate Specifications (Based on Predicted Effectiveness)

	Graduate High School (1)	Attend College (2)	Attend Four-Year College (3)	Historical Graduation Rate (4)	Persist 1st Year (5)	Composite Index (6)
(A) Kane & Staiger						
Composite Measure Effectiveness	0.025***	0.017**	0.018***	0.014***	0.015**	0.090***
	(0.007)	(0.007)	(0.005)	(0.003)	(0.006)	(0.021)
Effectiveness for Relevant Outcome	0.022***	0.028**	0.039***	0.023***	0.024	0.090***
	(0.006)	(0.009)	(0.008)	(0.005)	(0.020)	(0.021)
(B) Chetty, Friedman & Rockoff						
Composite Measure Effectiveness	0.018***	0.012*	0.013**	0.012**	0.013**	0.079**
	(0.005)	(0.006)	(0.005)	(0.004)	(0.005)	(0.027)
Effectiveness for Relevant Outcome	0.019***	0.014***	0.008*	0.009*	0.017**	0.079**
	(0.005)	(0.004)	(0.004)	(0.004)	(0.006)	(0.027)
(C) Logit (Odds Ratios)						
Composite Measure of Effectiveness	1.179***	1.080***	1.106***		1.079***	
	(0.031)	(0.018)	(0.021)		(0.020)	
Effectiveness for Relevant Outcome	1.147***	1.084***	1.139***		1.032	
	(0.030)	(0.024)	(0.023)		(0.034)	
N	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 cohort. 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. Estimates in panel (A) are based on the methods described in Kane & Staiger (2008). Estimates in panel (B) are based on the methods described in Chetty, Friedman & Rockoff (2014). Estimates in panel (C) follow the methods from Kane & Staiger (2008) but use a logit specification. In each panel, the first row shows how a counselor's predicted effectiveness, as measured with the composite index, is related to educational attainment. The second set of results in each panel show how outcome-based measures of predicted effectiveness are related to educational attainment.

Table A.12: Impact of Counselor Effectiveness with School Effects Included

	Graduate High School (1)	Attend College (2)	Attend Four-Year College (3)	Historical Graduation Rate (4)	Persist 1st Year (5)	Composite Index (6)
(A) Relevant Outcome						
Effectiveness (SD)	0.024***	0.036***	0.055***	0.047***	0.036***	0.110***
	(0.004)	(0.003)	(0.002)	(0.002)	(0.004)	(0.008)
(B) Overall Effects						
Composite Index	0.010**	0.020***	0.041***	0.042***	0.023***	0.110***
	(0.003)	(0.004)	(0.005)	(0.004)	(0.004)	(0.008)
(C) Indices of Effectiveness						
Cognitive Skills	0.004	0.002	0.004	0.002	0.000	0.026***
	(0.003)	(0.004)	(0.003)	(0.002)	(0.003)	(0.007)
Non-Cognitive Skills	0.005*	0.006**	-0.003	-0.000	0.003	0.034***
	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.009)
College Readiness	0.015***	0.017***	0.018***	0.005***	0.016**	0.048***
	(0.004)	(0.004)	(0.004)	(0.001)	(0.005)	(0.010)
College Selectivity	-0.009***	-0.000	0.027***	0.043***	0.007	0.049***
	(0.002)	(0.003)	(0.004)	(0.003)	(0.004)	(0.010)
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 cohort. 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 composite 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.13: Correlation Between Value-Added Measures

	Indices							
	Composite	Non-Cognitive Skills	Cognitive Skills	College Readiness	College Selectivity	Education	Graduate High School	Attend Four-year College
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(A) Indices								
Composite Index	1.000							
Non-Cognitive Skills	0.605	1.000						
Cognitive Skills	0.376	0.086	1.000					
College Readiness	0.908	0.474	0.241	1.000				
College Selectivity	0.660	0.154	0.272	0.467	1.000			
Education	0.788	0.311	0.258	0.627	0.633	1.000		
(B) Outcomes								
Graduate HS	0.682	0.373	0.164	0.617	0.339	0.776	1.000	
Four-Year College	0.671	0.189	0.334	0.486	0.720	0.863	0.422	1.000
Highly Selective College	0.267	-0.020	0.105	0.144	0.714	0.165	0.057	0.221

Notes: (*p<.10 **p<.05 *** p<.01). Estimates indicate the correlation of counselor value-added measures. These are the empirical Bayes estimates of counselor effects, estimated from models with fixed effects for the first letter of the student's last name, school, grade and cohort. They are based on the first counselor to which a student is quasi-randomly assigned. and they also account for 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. All measures of effectiveness are in standard deviation units. Panel (A) measures effectiveness with indices constructed based on weights from principal components analysis. Panel (B) measures effectiveness based on individual student outcomes. These estimates may overstate the true correlations since the same students are used in each measure of effectiveness.

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)	Composite Index (6)
(A) Gender Match						
Gender Match	-0.004*	-0.004	-0.005	-0.000	-0.003	-0.005
	(0.002)	(0.004)	(0.003)	(0.000)	(0.004)	(0.005)
Female Match	-0.002	-0.003	-0.000	0.000	-0.001	0.006
	(0.004)	(0.005)	(0.005)	(0.000)	(0.006)	(0.009)
Male Match	-0.007*	-0.005	-0.011**	-0.000	-0.007	-0.018**
	(0.004)	(0.005)	(0.004)	(0.000)	(0.005)	(0.008)
N	142,161	142,161	142,161	142,161	121,041	142,161
(B) Educator Experience						
Teacher	-0.013*	-0.010	-0.005	-0.000	-0.008	-0.033*
	(0.007)	(0.006)	(0.005)	(0.000)	(0.006)	(0.018)
Supervisor	-0.005	-0.011	-0.022***	-0.000**	-0.009	-0.040***
	(0.005)	(0.007)	(0.008)	(0.000)	(0.006)	(0.011)
N	135,659	135,659	135,659	135,659	115,037	135,659
(C) Years Experience (Grade 12)						
Novice	0.009*	0.008	0.013	0.004	0.013	-0.004
	(0.005)	(0.008)	(0.009)	(0.005)	(0.009)	(0.017)
Log(Years)	-0.055***	-0.055***	-0.055***	-0.055***	-0.054***	-0.055***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.012)	(0.011)
N	114,285	114,285	114,285	114,285	97,965	114,261

Notes: Heteroskedasticity robust standard errors clustered by counselor are 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. Panel (C) defines years of experience as the number of years a counselor has worked in MA (appears in the state's HR records since 2008) as of a student's 12th grade year.

Table A.15: Impact of Counselor's College

	Attend Four-Year (1)	Attend In-State (2)	Attend Public (3)	Attend Large (4)	Small Private (5)	College's Grad Rate (6)	Highly Selective (7)	Elite (8)
(A) Overall								
Coll in MA	0.009	0.018**	0.005	-0.004	0.009*	0.000**	0.002	0.007***
	(0.007)	(0.007)	(0.008)	(0.004)	(0.005)	(0.000)	(0.003)	(0.003)
Large Coll	0.013*	0.003	-0.004	0.011**	0.005	0.000	0.009***	0.001
	(0.008)	(0.008)	(0.008)	(0.004)	(0.006)	(0.000)	(0.003)	(0.002)
Small Priv Coll	0.003	-0.000	0.007	0.002	-0.003	-0.000	-0.002	-0.003
	(0.007)	(0.009)	(0.008)	(0.004)	(0.006)	(0.000)	(0.004)	(0.003)
Public Coll	0.009	0.011	0.008	-0.002	0.002	0.000	0.001	0.003
	(0.007)	(0.007)	(0.007)	(0.005)	(0.005)	(0.000)	(0.004)	(0.002)
Private Coll	-0.009	-0.011	-0.008	0.002	-0.002	-0.000	-0.001	-0.003
	(0.007)	(0.007)	(0.007)	(0.005)	(0.005)	(0.000)	(0.004)	(0.002)
High Sel. Coll	-0.008	0.001	-0.007	0.001	-0.000	-0.000	-0.000	0.003
	(0.009)	(0.007)	(0.007)	(0.008)	(0.005)	(0.000)	(0.005)	(0.004)
Elite Coll	-0.017	-0.017*	-0.011	-0.004	-0.009	-0.000	0.006	0.015**
	(0.012)	(0.010)	(0.007)	(0.010)	(0.007)	(0.000)	(0.008)	(0.006)
N	29,007	28,998	28,998	29,007	28,998	29,007	29,007	29,007
(B) Among College Attendees								
Coll in MA	0.000	0.008	-0.011	-0.007	0.009	0.000	0.005	0.016***
	(.)	(0.009)	(0.010)	(0.009)	(0.008)	(0.000)	(0.006)	(0.005)
Large Coll	0.000	0.011	0.008	0.016**	-0.004	0.000**	0.011**	-0.002
	(.)	(0.010)	(0.008)	(0.008)	(0.009)	(0.000)	(0.005)	(0.004)
Small Priv Coll	0.000	-0.012	-0.007	0.005	-0.006	-0.000	-0.005	-0.006
	(.)	(0.011)	(0.009)	(0.008)	(0.008)	(0.000)	(0.006)	(0.005)
Public Coll	0.000	0.009	0.010	-0.006	-0.005	0.000	0.002	0.007
	(.)	(0.007)	(0.008)	(0.009)	(0.006)	(0.000)	(0.007)	(0.004)
Private Coll	0.000	-0.009	-0.010	0.006	0.005	-0.000	-0.002	-0.007
	(.)	(0.007)	(0.008)	(0.009)	(0.006)	(0.000)	(0.007)	(0.004)
High Sel. Coll	0.000	0.006	-0.000	0.006	0.001	-0.000	-0.001	0.005
	(.)	(0.009)	(0.008)	(0.012)	(0.008)	(0.000)	(0.007)	(0.006)
Elite Coll	0.000	-0.018	-0.001	0.002	-0.008	0.000	0.012	0.023***
	(.)	(0.012)	(0.010)	(0.012)	(0.010)	(0.000)	(0.009)	(0.007)
N	15,588	15,588	15,588	15,588	15,588	15,588	15,588	15,588

Notes: Heteroskedasticity robust standard errors clustered by counselor are 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: 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	0.006	0.009	0.010	0.008	0.000	0.028
	(0.009)	(0.009)	(0.007)	(0.004)	(0.000)	(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.17: 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)
Effect on:					
Education Index	1				
Graduate High School	0.801	1			
Attend College	0.949	0.701	1		
Attend Four-Year	0.911	0.561	0.834	1	
Attend Four-Year	0.883	0.413	0.780	1	
Historical Graduation Rater	0.885	0.617	0.771	0.938	
Evaluation Rating	-0.203	-0.168	-0.190	-0.151	-0.194

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). 71 counselors fit this criteria. 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.

B Test of Specialization

In this section I formally examine whether counselors 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, 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.

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, 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.

$$H1_0 : \Delta_z = (\mu_{overall} - \mu_{outcome_z})^2 = 0 \tag{11}$$

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.

$$H2_0 : \delta_{xz} = (\mu_{outcome_x} - \mu_{outcome_z})^2 = 0 \tag{12}$$

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 B.1 shows that there are some differences in counselors' average effectiveness and their effectiveness for individual indices, but none of these differences are significant. The largest differences are for non-cognitive skills, cognitive skills, and highly selective college attendance.

The remaining rows in Table B.1 test the second hypothesis. They also indicate some differences in effectiveness across the dimensions but none of these differences are large or statistically significant. Thus, in general, the same counselors who improve college readiness and attendance also tend to improve college selectivity and skills in high school.

All together, these results indicate that there is not much specialization apparent across counselors different responsibilities. I also do not find much evidence of specialization over certain types of students (based on academic achievement or income).

Table B.1: Test of Specialization Over Outcomes

	Non-Cognitive Skills	Cognitive Skills	College Readiness	College Selectivity	Education Index	Highly Selective
(A) Overall						
Composite Index	0.319	0.322	0.177	0.272	0.244	0.371
(B) Relative to Indiv. VA						
Non-Cognitive Skills	0.000					
Cognitive Skills	0.271	0.000				
College Readiness	0.382	0.371	0.000			
College Selectivity	0.376	0.287	0.358	0.000		
Education Index	0.394	0.344	0.335	0.284	0.000	
Highly Selective College	0.351	0.241	0.419	0.202	0.384	0.000

Notes: These estimates indicate the absolute value of the differences in a counselor's estimated effect for the outcomes, in standard deviation units. The stars are from a chi-square test for whether the differences are statistically significant from zero. (*p<.10 **p<.05 *** p<.01). None of the differences are significant at the 10% level. 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 cohort, 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.